Study on Advanced In-Core Fuel Management for Pressurized Water Reactors Using Loading Pattern Optimization Methods(Dissertation_全文)

AUTHOR(S):

Yamamoto, Akio

STUDY ON ADVANCED IN-CORE FUEL MANAGEMENT FOR PRESSURIZED WATER REACTORS USING LOADING PATTERN OPTIMIZATION METHODS

AKIO YAMAMOTO

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CHAPTER 3. LOADING PATTERN OPTIMIZATION USING HYBRID GENETIC ALGORITHMS

CHAPTER 1

INTRODUCTION

1.1 Background

Commercial nuclear reactors have increasing the importance in the role of power generation during past few decades. Actually, the nuclear power accounts for approximately 30% of the Japanese electric power supply, today. Since there is little energy resources in Japan, the nuclear power is considered to be one of the stable and indispensable energy sources.

The cost of nuclear power remains lower compared with that of other sources, such as the fossil or hydropower. However, due to improvements in the technology of utilizing the fossil power, especially in an advanced combined cycle (ACC) technology using liquid natural gas (LNG), the superiority of nuclear in the cost of power generation is becoming smaller. To keep the nuclear power competitive, reduction of the power generation cost is desirable.

The cost of nuclear power mainly consists of the nuclear fuel cost, the capital cost, the maintenance cost and the replacement power cost during the inspection period. So there are several ways to reduce the cost of nuclear power. In this thesis, improvements of in-core fuel management methods, which can reduce the nuclear fuel cost, will be discussed. Note that the nuclear fuel cost amounts to approximately 20% in the whole nuclear power cost as shown in Table 1-1[1] [2]. Since the capital cost, which corresponds to the cost of plant construction, is fixed, improvement of the nuclear fuel cost is considered to be one of the important point to reduce the cost of nuclear power generation.

The nuclear fuel cost essentially depends on reactor types, specifications of fuel

assemblies, the in-core fuel management and reactor operating methods. One of the major tasks of in-core fuel management is to determine a fuel loading pattern. The fuel loading pattern is an arrangement of fuel assemblies in a reactor core, and its design is based on a quite complex combinatorial optimization as will be discussed later in this chapter. Though the loading pattern optimization is one of the primary factors to improve the fuel cycle cost, it was difficult to find practical solutions because of its stiff and complicated nature. Therefore, engineers, who are responsible to the in-core fuel management, optimize the loading pattern in every cycle using their state-of-art techniques. Since the optimizations by engineers are mainly based on a trial-and-error approach, a practical limit exists on their optimization capabilities.

Recently, high performance computers, such as engineering workstations (EWS) or personal computers (PCs), are being widely used and the calculation cost is rapidly decreasing. Thanks to these powerful computers, practical and robust optimization theories are being developed and being applied for many industrial problems[3].

For these backgrounds, this thesis treats optimization problems of the fuel loading pattern and its applications to the practical in-core fuel management, aiming to reduce the nuclear fuel cost. The target reactor type in this thesis is a pressurized water reactor (PWR), which shares around a half of the commercial reactors in Japan.

1.2 Basics of in-core fuel management for PWR

1.2.1 Description of a PWR core from a viewpoint of in-core fuel management

A PWR core can be considered as an array of fuel assemblies from a viewpoint of neutronics design. Figure 1-1 shows a PWR core of Westinghouse three-loop type

that contains 157 fuel assemblies. A fuel assembly is consists of fuel pins, which are arranged in a square grid of 17 by 17 as shown in Fig. 1-2. The dimension of the fuel assembly is approximately 21cm×21cm×400 cm (depth × width × height). Note that the fuel assembly also includes guide thimbles for control rods (rod cluster control, RCC) and instrumentation thimble for measurement of in-core power distribution.

A thermal output of the Westinghouse three-loop type PWR is 2650MW, so the fuel assembly generates about 17MW when the power density of the fuel assembly is equal to an average value in the reactor. Note that, since the assembly power density depends on its reactivity and the fuel loading pattern as will be discussed in Sec. 1.2.4, the actual power density is different in each assembly. Here, the reactivity of the fuel assembly is mainly depends on its cumulative thermal output; the burnup.

In accordance with the current Japanese regulations, the periodical inspection is performed almost once a year. During this inspection, about one-third of burnt fuel assemblies are discharged from the core as spent fuel assemblies and the fresh fuel assemblies are loaded into the core instead of the discharged fuels. This kind of refueling strategy is called as a multi-batch loading. The concept of the multi batch loading is shown in Fig. 1-3 for reference.

Since the ^{235}U enrichment of fresh fuel assemblies (feed enrichment) is fixed in Japan, the number of fresh fuel assemblies is determined according to the expected operating length of next cycle. The discharged fuel assemblies are usually selected according to their burnup; well-burnt fuels are discharged with a higher priority.

As mentioned above, the neutronics characteristics of the fuel assemblies depend on not only the specification of fuel assemblies such as the ^{235}U enrichment or the content of burnable poisons, but also their burnup. Therefore, various fuel assemblies with different neutronics characteristics are loaded into the core under

the multi-batch refueling strategy as shown in Fig. 1-4.

1.2.2 Design process of a fuel loading pattern

The outline of the in-core fuel management for PWR is shown in Fig. 1-5. When the numbers of fresh fuel assemblies and burnt fuel assemblies are fixed, a core designer can define a fuel loading pattern. Since the nuclear characteristics of individual burnt fuel assemblies are different, number of possible patterns for the fuel arrangement in the core accounts for enormous one. For example, Table 1-2 shows a typical enumeration number of fuel arrangements in the Westinghouse type four-loop reactor, which contains 193 fuel assemblies.

During the loading pattern design process, the designer often assumes octant or quarter core symmetry shown in Fig.1-1 and several empirical rules (heuristics) about the loading pattern to reduce the possible combination number. Unfortunately, the enumeration number is still too large to calculate all possible loading patterns.

The safety concern is a most important point for the characteristics of the fuel loading pattern. In order to satisfy the safety criteria, various constraints should be considered during the loading pattern design process as will be discussed in Sec. 1.3.2. Since the economic aspect is also important in the practical application, various objectives should be taken into account to maximize the fuel utilization efficiency as will be discussed in Sec. 1.3.2.

1.2.3 Impact of a loading pattern on the core characteristics

In the boiling water reactor (BWR), the in-core power distribution can be adjusted by the control rods, which are inserted into the gap between assemblies from the reactor bottom to top. Though PWR also has rod cluster controls (RCCs),

they are generally used to shutdown the reactor; RCCs are not used to control the in-core power distribution.

Consequently, the power distribution in the PWR core essentially depends on the fuel loading pattern itself. Since the power distribution is a key parameter for the reactor core safety and the economics, the loading pattern is considered to be the most important point in the core design.

For reference, Fig. 1-6 shows three different PWR cores that consist of the same fuel inventory; only the fuel loading pattern is different among these cores. The (a) core violates the current safety limit for the radial peaking factor, which should be less than 1.480. Since the radial peaking factor affects to the maximum pellet temperature and so on, the integrity of the fuel pin in the (a) core cannot be guaranteed. The (b) core satisfies the safety criteria on the peaking factor, so the (b) core is acceptable. The (c) core also satisfies the safety criteria on the peaking factor. Moreover, the discharge burnup of the (c) core is much higher than that of the (b) core.

The discharge burnup is a cumulative thermal output of spent fuel assemblies, hence a higher discharge burnup indicates an effective usage of nuclear fuel. For example, a 5% difference in the discharge burnup is estimated to result in hundreds millions of Yens in the fuel cost per a cycle.

It should be noted that, to simplify the discussion, only the radial peaking factor is considered as the constraint in the above explanation. However, in the practical loading pattern design, various constraints such as limitations on the maximum fuel assembly burnup, the moderator temperature coefficient, the reactor shutdown margin and so on, must be considered. Hence the situation of the actual loading pattern design is much more complicated.

The observation described above reveals the importance of optimization on the

fuel loading pattern. Namely, since the fuel loading pattern greatly affects the safety and the economics of reactor cores, its optimization becomes quite important from the industrial point of view[4].

1.2.4 In-core and ex-core fuel managements

The multi-batch loading can attain the higher discharge burnup compared to the single-batch loading[5]. However, the multi-batch loading makes the loading pattern optimization more complex one in two aspects. At first, since every burnt fuel assembly has different neutronics characteristics, the enumeration number of possible fuel placements in a core becomes enormous one as mentioned in Sec. 1.2.2. Secondary, since a fuel assembly stays in-core during several operating cycles, coupling effects between consecutive cycles should be considered.

For example, in the single-batch loading, all fuel assemblies are discharged at the end of cycle. This means that each cycle is independent; there is no interference between successive cycles. Therefore a designer can apply an identical fuel loading pattern in every cycle, when the cycle lengths are the same among these cycles. On the other hand, fresh fuel assemblies should be loaded with burnt fuel assemblies in the multi-batch loading. Since the burnup of fuel assemblies depends on the loading patterns of previous cycles, the designer should consider the loading patterns of successive several cycles simultaneously.

Unfortunately, the loading pattern optimization problem of multiple cycles is far beyond the ability even for the latest computers. So the current fuel management is mainly divided into two parts, which are an in-core fuel management and an ex-core fuel management, by omitting cycle by cycle coupling effect. The in-core fuel management is mainly responsible for a design of a loading pattern and a series of follow-up calculations of a core during the reactor operation.

On the other hand, the ex-core fuel management is mainly responsible for defining an operating cycle length and selecting the discharge fuels, and so on.

This thesis addresses not only to the loading pattern optimization for a single cycle that is included in the in-core fuel management, but also to the optimization for the multiple cycles that is included in both the in-core and the ex-core fuel managements.

1.3 Descriptions of the loading pattern optimization problem

1.3.1 Features

Features of the loading pattern optimization problems are summarized as follows:

(1) It is one of the combinatorial optimization problems since the loading pattern defines combination of individual fuel and loading position in the core. In the combinatorial problem, a quality of a solution, which is represented by an objective value, is discrete among solutions. Therefore, gradient information of objective values, which can indicate a direction to improve a solution, is very hard to be obtained exactly. Hence the combinatorial optimization problem is considered to be more difficult than that of the continuous functions. Note that the objective value is evaluated by core characteristics using an objective function in the loading pattern optimization.

(2) As discussed in Sec.1.2.2, the enumeration number of the loading patterns reaches really an astronomical one.

(3) The nature of objective values has non-linearity; an objective value cannot be obtained by the superposition of the other objective values. For example, let's consider the assembly exchange shown in Fig. 1-7. Perturbation on the power

distribution caused by the assembly exchanges of (a) cannot be obtained by adding the perturbation by the exchange (b) and that by the exchange (c). Consequently, core calculations must be performed for all candidate patterns. Therefore, the calculation time becomes incredibly longer.

(4) Since the nature of objective values has non-linearity, there are many local optima in the solution space. Figure 1-8 shows the concept of the local optima and the global optimum. Ordinary optimization methods such as liner programming cannot escape from local optima, since their search progress according to the gradient of the objective value in the solution space. Figure 1-9 provides behavior of the objective value on the actual loading patterns, which will treat at a benchmark calculation in Chap. 3. From Fig. 1-9, a complex structure of the objective value in the solution space and many local optima can be observed.

(5) Since the nuclear reactor has a potential of large hazard, the safety concern has a top priority in the design process. Therefore, various constraints should be satisfied during the loading pattern design, as will be discussed in the next section.

From the above reasons, the loading pattern optimization problem is considered to be quite difficult.

1.3.2 Objectives and Constraints

In order to maintain the safety of nuclear reactors, various restrictions should be considered during the loading pattern design as mentioned in the previous sections. Major restrictions on the neutronics characteristics are as follows:

(1) Limitation on the radial peaking factor, which is defined by the relative peak power of a fuel rod in the core. Here the power of a fuel pin is axially integrated. The limitation on the radial peaking factor is settled to prevent the fuel failure caused by DNB. Since the radial peaking factor greatly depends on the fuel loading pattern, this restriction is considered as a primary target during the loading pattern design.

(2) Limitation on the maximum linear heat generation, which is the heat generation per a unit length of a fuel rod. This restriction is closely related to the maximum pellet temperature at transient incidents or loss-of-coolant accidents. In order to obtain the maximum linear heat generation, an axial power distribution is necessary. However, since two-dimensional core calculations are usually adopted for the loading pattern optimization because of the computation time, the maximum linear heat generation cannot be estimated directly. Fortunately, when the restriction on the radial peaking factor is satisfied, the restriction on the maximum linear heat generation is usually satisfied. So this limitation is not considered in the most calculations of the loading pattern optimization.

(3) Limitation on the maximum burnup of a fuel assembly, which is cumulative thermal output per unit heavy metal inventory. Since the corrosion and the neutron irradiation reduce the strength of fuel clad as increasing burnup, the limitation on the maximum burnup must be taken into account. The fuel burnup also much depends on the fuel loading pattern, so the great care should be paid when the margin to the limit of maximum burnup is small.

(4) Limitation on the moderator temperature coefficient (MTC), which is reactivity change due to the perturbation on the moderator temperature. To maintain the inherent safety, the reactor core must have a negative reactivity feedback; the negative reactivity must be inserted intrinsically when the reactor power

increases. In Japan, MTC must be negative throughout the power operation. In general, the longer cycle operation increases the boron concentration at the beginning of cycle and MTC tends to move toward a positive value. Though MTC depends on the fuel and burnable poison inventory, it also depends on the fuel loading pattern. Therefore, MTC should be considered at the loading pattern design, especially in the longer cycle.

(5) Limitation on the radial power tilt, which represents power imbalance along the symmetric line shown in Fig. 1-1. Since the radial power tilt increases the radial peaking factor, it should be reduced as lower as possible. Fortunately, the radial power tilt becomes significant only for loading of asymmetric fuel pairs in the core. The radial power tilt should be taken into account in such a case.

(6) Limitation on the reactor shutdown margin (SDM), which means subcriticality of the core at the one-rod stuck configuration. Here the one-rod stuck configuration means all RCCs are fully inserted in the core except one RCC that has the largest reactivity worth. The shutdown margin guarantees the subcriticality during the transient of cooling accidents such as the steam line break. Note that when the core is cooled because of some accidents, the positive reactivity will be inserted because of the negative MTC of the core. Though the SDM can be estimated by the two-dimensional core calculation, it requires full-core calculation to simulate the one-rod stuck configuration accurately. Furthermore, many stuck rod configurations should be calculated even if the core symmetry is considered. Note that the ordinary calculations are performed for the quarter core geometry using the core symmetry. Since the SDM calculation requires much computation time, it is difficult to incorporate the SDM calculation into the loading pattern optimization. Though SDM can be partially controlled by some heuristic rules on the fuel loading pattern, e.g. the burnt fuel

should be placed at the stuck rod position, its estimation is still one of the major issues in the loading pattern optimization problem.

(7) Limitation on other safety parameters, which are necessary to execute accident analyses, should be taken into account. For example, the uncontrolled RCC withdrawal, the RCC drop, the RCC ejection, and so on, must be analyzed and safety parameters should be confirmed. Fortunately, these parameters are usually adequate when the limitation on the radial peaking factor and SDM are satisfied. Therefore, these parameters are not usually included in the loading pattern optimizations as the constraints.

(8) Other limitations from plant structures must be considered sometimes. For example, Nuclear Regulatory Committee (NRC) recommended the burnup limitation at the RCC positions recently. This is a countermeasure for the incomplete RCC insertion incident observed in some of reactors in USA, as will be discussed in Chap. 4. Another example is related to the neutron irradiation for the reactor vessel. Since the ductility of the reactor vessel decreases as increasing neutron irradiation, a loading pattern that reduces the neutron irradiation for the vessel is desirable. This is particularly important in the old reactors whose vessel has much irradiated by neutrons.

Major objectives in the loading pattern optimization are as follows:

(1) Maximization of the cycle length under the fixed feed enrichment and the fixed number of fresh fuel.

(2) Maximization of the discharge burnup under the fixed feed enrichment and the fixed number of fresh fuel.

(3) Minimization of the number of fresh fuel under the fixed cycle length and the

fixed feed enrichment.

(4) Minimization of the enrichments under the fixed cycle length and the fixed number of fresh fuel.

Here the objectives mean that these values are not treated as constraints, but the loading pattern should be designed to maximize or minimize these values from the economical point of view.

In Japan, the feed enrichment is usually fixed to a unique value, so the objective (4) is out of consideration. The objectives (1) and (3) have almost the same context, though the objective (2) has somewhat different meanings on the loading pattern design for the single cycle. The reason is the trade-off relationship between the cycle length and the discharge burnup. For example, when the cycle length is maximized, the discharge burnup tends to become lower in the single cycle optimization.

This trade-off makes interesting results in the multiple-cycle loading pattern optimization, as will be discussed in Chap. 5.

1.3.3 Traditional Approach

Since the loading pattern optimization is highly required from the safety and economical points of view, many researchers have studied various approaches during the past few decades. Though an well-organized historical review of the loading pattern optimization is provided in Ref. (6), some of the major approaches are described here to make an image about the loading pattern optimization.

The linear programming is a popular optimization method and widely applied to the industrial purpose. The optimization by linear programming is formulated as follows:

$$O = \sum_{l,l'} a_{ll'} X_{ll'} \quad (1 \le l \le N, 1 \le l' \le N) \cdots\cdots (1)$$

where

O : Objective value that represents the core performance.

$a_{ll'}$: Sensitivity parameter of the objective value caused by the assembly exchange between l and l'.

$X_{ll'}$: Flags of assembly swap between l and l'. When the exchange between l and l' exsists, $X_{ll'}$ becomes 1, otherwise 0.

The $X_{ll'}$ can be determined from Eq.(1) under several constraints. Once $X_{ll'}$ has determined, the optimum loading pattern is obtained by exchanging fuel assemblies according to the flag represented by $X_{ll'}$.

Though the linear programming is simple, it has several difficulties for applying it to the loading pattern optimization problems as follows:

(1) The linear programming requires sensitivity parameters for the optimization. Therefore, enormous sensitivity parameters should be calculated when a problem treats various constraints. For example, sensitivity coefficients for the radial peaking factor and the maximum burnup are different, so these coefficients should be prepared before the optimization.

(2) The linear programming can treat the "linear" problem that allows the superposition of the solutions. Unfortunately, the loading pattern optimization problem has non-linearity, so the linearization is required. By applying the linearization, the obtained "optimum solution" is no more the optimum exactly because of the approximation error. To minimize this approximation error, a successive linear programming is often used. However, the since successive linear programming requires many sensitivity coefficient calculations, the calculation time tends to become much longer.

(3) The linear programming is based on the gradient projection; the search

progresses only to improve the objective value. Therefore, the linear programming cannot accommodate the multi-modality that is essential in the loading pattern optimization.

The direct search method, which is based on the multiple shuffles of fuel assemblies, is also studied by several researchers. The direct search method is applied to a loading pattern optimization problem as follows:

(a) Assume an initial solution,
(b) Swap fuel assemblies randomly or according to the heuristic rules to generate a candidate of solution,
(c) Estimate the objective value of the candidate,
(d) If the candidate improves the objective value, the swap is accepted. Otherwise the swap is rejected and another swap is tried,
(e) Repeats the procedure from (b) to (d) until the improvement of the objective value converges.

The direct search method does not require the sensitivity coefficient, but the core characteristics should be estimated for every loading pattern. Since the direct search method only accepts the improved solutions during the search process, it cannot treat the multi-modality. Detailed discussion about this point will be performed in Chap.2.

Since the engineer well optimizes the loading pattern using their state-of-art knowledge, the artificial intelligence, which performs the search based on the rule sets, was considered to be efficient for this problem. Examples of the rule set are as

follows:

(1) High reactivity fuels and low reactivity fuels should be placed side by side in the interior of the core to reduce the power peaking factor.
(2) A fresh fuel that does not contain burnable poisons is not loaded in the interior of the core; it should be loaded to the core periphery.

The artificial intelligence performs quite well under the typical situations that can be accommodated by its "knowledge". The "knowledge", however, sometimes disturbs the optimization. For example, the reactivity of a burnt fuel assembly is low, so it is often loaded besides a high reactivity fuel in the interior of the core to suppress the power peaking factor. Therefore, a loading pattern optimization code that is implemented with this knowledge will put the burnt fuel assembly in the interior of the core. But when the cycle length is too long, the well-burnt fuels should be placed at the core periphery to satisfy the limitation of the maximum burnup. Note that the power density of the fuel at the core periphery tends to be lower because of the neutron leakage from the core.

The above example suggests that the appropriate rule set is highly sensitive to the miscellaneous analysis conditions such as the cycle length, the inventory of the fuel assemblies, and so on. To respond almost all situations that include exceptional cases, enormous rule sets should be implemented. Moreover, new rule sets should be implemented when the new-type fuel assemblies are loaded. However, the development and implementation of rule sets are considered to require an extensive work. Consequently, the artificial intelligence lacks the robustness that indicates the toughness of the method; the artificial intelligence cannot perform optimization under unexpected situations.

1.3.4 Advanced approach

In the previous section, some traditional optimization methods were briefly reviewed. However, these methods have inherent shortcomings that are difficult to overcome in practical applications. Therefore, the loading pattern optimization had remained in the academic area for a long time.

Recently, thanks to the rapid improvement of the computer hardware, emergent computing methods are gaining their admiration[3] [7]. They provide the self-organized behaviors from estimations for local situation; it does not utilize the knowledge or rules that controls an overall system. The emergent computing methods are based on a completely different approach from most of the traditional ones. The traditional methods utilize so-called top-down approach that defines the behavior of system from the top to bottom. On the other hand, emergent computations define their behaviors from the bottom to top.

The relation between the traditional optimization and the emergent computation corresponds to the relation between the neutron transport calculation based on the Boltzman equation and that by the Monte Calro method. In the emergent computation methods, Genetic algorithms and simulated annealing methods are the popular ones.

Since the emergent computations utilize only estimations of the local situation, it is quite robust. For example, consider a problem about the burnt-fuel discussed in the previous section. The artificial intelligence approach defines the fuel loading pattern according to the rule sets and the information such as the cycle length or the fuel inventory. In the emergent computation, a candidate obtains a good objective value if the maximum burnup does not violate the limitation, otherwise it obtains a bad value. The search progresses utilizing these objective values.

Therefore, the emergent computation can easily respond various constraints or objectives. A detail description of the emergent computation will be provided in Chap. 2.

Note that since the emergent computations require many trial calculations to find out the optimum or the near-optimum solution, the computation time tends to become longer. However, progresses on the computer hardware make such calculations feasible.

Recently, the emergent computations such as the simulated annealing were applied to the loading pattern optimization problems and showed good feasibility[8],[9].

The development of an efficient optimization method for the loading pattern using the emergent computation methods is one of the major topics in this thesis and will be discussed in Chap. 2.

1.4 Purpose of this thesis

The efficient utilization of nuclear fuel is important to reduce the cost of nuclear power and to save the limited Uranium resources. As mentioned in the previous sections, the fuel loading pattern, which means the fuel arrangement in the core, has a quite large impact on the core performance from viewpoints of safety and economics. Therefore, there are strong needs for its optimization from an industrial point of view.

Since the loading pattern optimization is a stiff problem, the traditional optimization methods cannot cope with it. However, the emergent computations, which are based on the stochastic process, can make a breakthrough for this problem. Though the emergent computations are robust and applicable to practical problems, it takes a much computation time. Therefore, the first purpose of this

thesis is:

(1) To develop a more efficient optimization method for the fuel loading pattern. Here, the optimization method should be robust and applicable for the practical and industrial-scale problems.

Since the in-core fuel management requires various kind of data, a software workbench to manage these data is highly required especially in the multicycle analysis. There are several software tools for the in-core fuel management, though they were mainly designed to perform optimization for the single cycle. As mentioned in Sec. 1.2.4, an accurate analysis and optimization for the multiple cycles are important to reduce the overall fuel cycle cost. Therefore, second purpose of this thesis is:

(2) To develop a software tool for the in-core fuel management that has capability to treat loading pattern optimizations for successive multicycles. Furthermore, the software should be user-friendly for practical applications.

Though the true multicycle optimization that is necessary to perform simultaneous optimizations of the multiple cycles is far beyond the ability of today's computers, it is important to evaluate the effect of loading patterns for the whole multicycle performance. In the loading pattern optimization for a single cycle, the low-leakage loading pattern was considered to be desirable because it could attain a longer cycle length than the traditional out-in loading pattern. However, as mentioned in Sec. 1.3.2, the discharge burnup tends to become lower in the low-leakage loading pattern. Namely, a trade-off exists between the cycle length and the

discharge burnup. Therefore, the third purpose of this thesis is:

(3) To examine a desirable loading pattern strategy for the overall fuel cycle cost by evaluating the trade-off between the low-leakage strategy and the high-discharge burnup strategy.

These problems will be discussed through Chap.2 to Chap.5.

1.5 Contents of this thesis

This chapter provides basic concepts of the in-core fuel management for PWRs and a conceptual description of the loading pattern optimization problem for the better understanding about this thesis. This chapter also points out the backgrounds and the purposes of this thesis.

Chapter 2 describes the development and verification of loading pattern optimization methods[10]. As described in Sec. 1.3, the loading pattern optimization is a quite difficult problem, and requires novel optimization theories to make a breakthrough for the practical use. The genetic algorithm is applied to this problem since it is considered to be quite suitable to a complicated combinatorial optimization problem. The genetic algorithm is one of the optimization techniques whose concept is based on the evolution of life. According to the Darwinian theory, the survival of fittest and the crossover of chromosomes promote the life towards the adaptive direction. For the loading pattern optimization, a candidate of the loading pattern is treated as an individual, and the performance of the individual, which is defined by the core characteristics such as the cycle length and the radial peaking factor, defines the probability of survival or mating.

Though the genetic algorithm is powerful for the global search, its local search capability is rather poor. Therefore, a new hybrid optimization method, which combines genetic algorithms and the local search method, will be proposed. To verify the capability of the proposed optimization method, the quantitative comparison with other optimization methods such as the direct search or the simulated annealing, is performed and optimization results are compared with each other.

Chapter 3 provides calculated results of a benchmark problem using the hybrid optimization method that is proposed in Chap. 2. In the combinatorial optimization problem, a guarantee of the optimum solution can be obtained only through the exhaustive enumeration calculations. However, since the enumeration number accounts for an enormous one in the practical optimization problem, it is difficult to confirm the optimization capability that can find out the optimum solution.

A benchmark problem is set up assuming restrictions about the fuel placement in the core and simplifications of the fuel inventory. By evaluating all loading patterns in the benchmark problem, an optimum solution is identified. After that, the hybrid optimization method is applied to the benchmark problem and its capability is examined.

Chapter 4 describes the development and applications of INSIGHT, which is a software for the practical in-core fuel management[11]. The hybrid optimization method for the fuel loading pattern is used as a key technology in INSIGHT.

In the practical in-core fuel management, various data should be treated; these include the power distribution from the core calculation, the fuel loading history, the fuel burnup, and so on. Therefore, an integrated software, which realize a seamless management of these data, is highly desired especially in the multicycle analyses.

INSIGHT includes capabilities of the core calculation, the loading pattern optimization, the management of database, and so on.

INSIGHT is applied to the practical problem of in-core fuel management, and its capability is tested.

Chapter 5 describes the loading pattern optimization considering the coupling effect in the multiple cycles[12]. As mentioned in Sec.1.2.4, the fuel assemblies are loaded during several cycles. Though the optimization for the multiple cycles is desirable to reduce the overall fuel cost, it is far beyond the ability of today's computers, as mentioned before. Therefore, a cycle by cycle successive optimization is often used in the current in-core fuel management.

In Chap. 5, the equilibrium cycle is treated because it can be considered as the special case of the multiple cycle. Namely, the optimization of the equilibrium cycle is considered almost compatible with that of the multiple cycles.

A new optimization method for the equilibrium cycle is proposed since the optimization is somewhat complicated than that of the single cycle. Using the new optimization method and the successive multicycle optimization method developed in Chap. 4, strategy for the multiple cycle optimization is investigated.

Chapter 6 summarizes the results obtained through the course of this study, and a future view of this study is also provided.

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Table 1-1 Breakdown of typical nuclear power generation cost

Cost	Ratio	Note
Capital	70%	Fixed
Nuclear Fuel	20%	Depends on fuel specification, loading pattern, etc.
Maintenance and Operation	10%	Depends on plant operation, etc.
Total	100%	

Table 1-2 Enumeration number of the fuel loading pattern for Westinghouse 4 loop PWR

Constraints	Enumeration number	Estimated calculation time (year)
No symmetry, no intra-batch equivalence for fresh fuel	6.8E+358	2.1E+351
With quarter core symmetry, no intra-batch equivalence for fresh fuel	1.2E+61	3.8E+53
With octant core symmetry, no intra-batch equivalence for fresh fuel	6.2E+23	2.0E+16
With octant core symmetry, with intra-batch equivalence for fresh fuel	1.4E+20	4.5E+12

Note1:The number of fresh fuel assemblies is assumed to be 72, including 48 Gadolinia bearing fuels.
Note2:The calculation time is assumed to be 1 second/pattern.

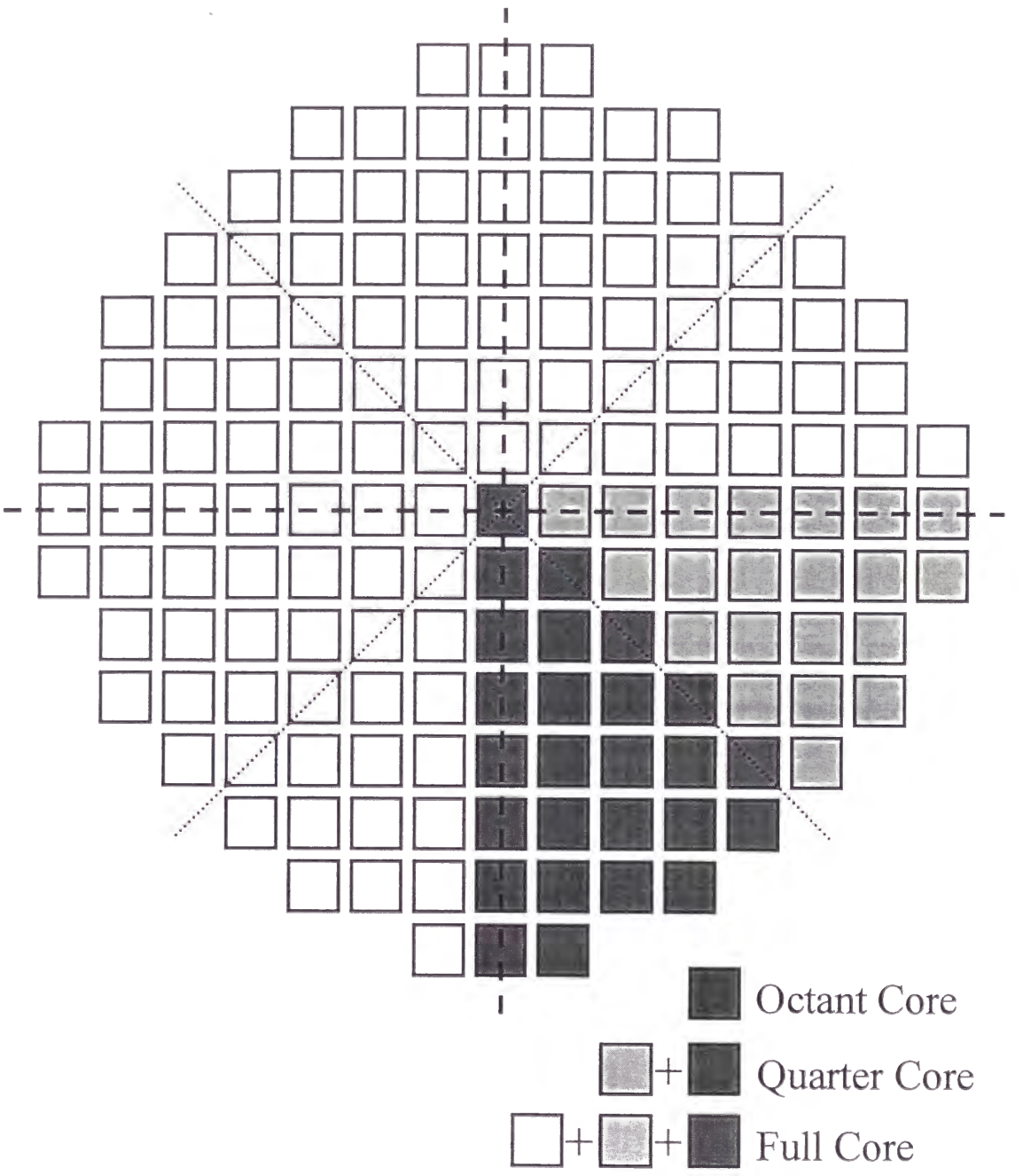


Fig. 1-1 A fuel arrangement of PWR core; Westinghouse three loop type

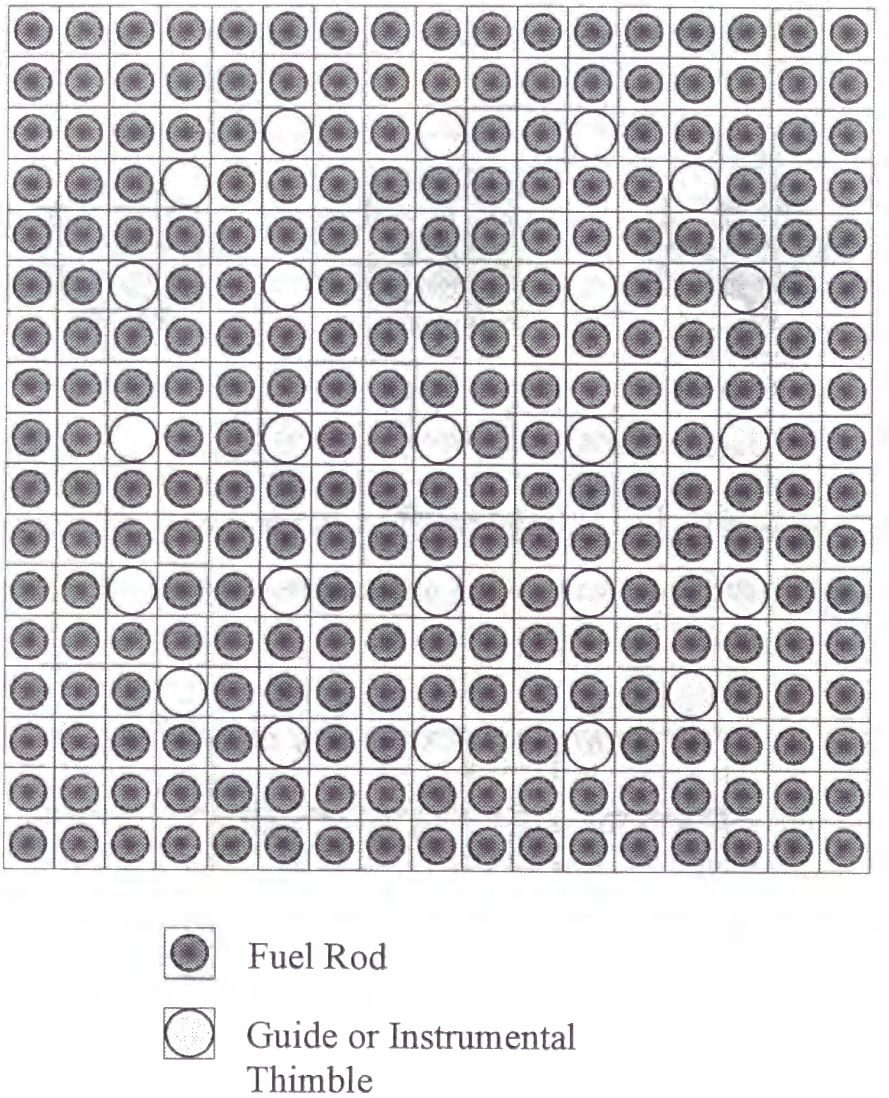
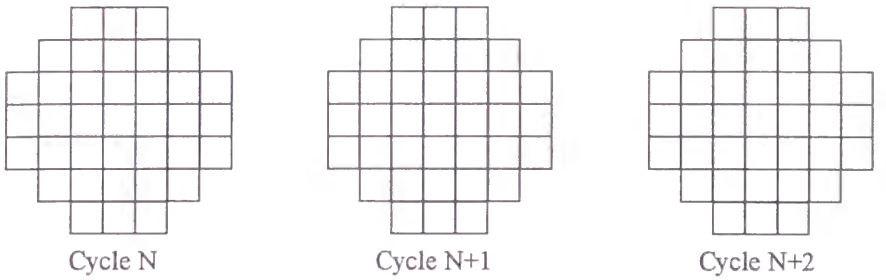
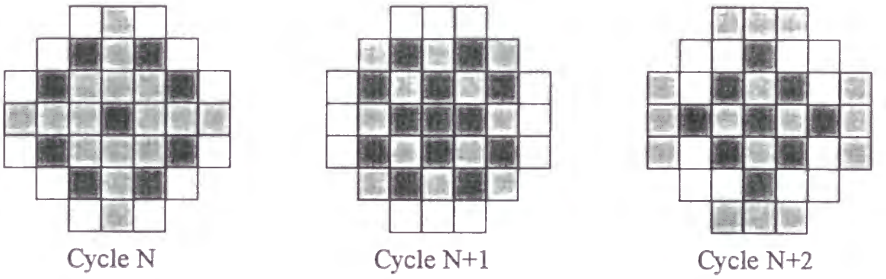


Fig. 1-2 Cross-sectional view of a fuel assembly; 17x17 type



(a) Concept of a single batch loading



(b) Concept of a multi-batch loading

Fig. 1-3 Concept of a single batch loading and a multi-batch loading

	H	G	F	E	D	C	B	A
8	2G 35.1	2 30.5	1G 19.7	2 25.8	2 30.5	1G 19.1	1G 19.1	2G 31.5
9	2 30.5	2 25.8	NG 0.0	1 12.5	NG 0.0	1 11.4	1G 20.0	N 0.0
10	1G 19.7	NG 0.0	1G 19.7	2G 30.5	2 30.4	NG 0.0	N 0.0	
11	2 25.8	1 12.5	2G 30.5	1G 19.3	NG 0.0	1 7.8	2G 32.2	
12	2 30.5	NG 0.0	2 30.4	NG 0.0	1G 19.3	N 0.0		
13	1G 19.1	1 11.4	NG 0.0	1 7.8	N 0.0			
14	1G 19.1	1G 20.0	N 0.0	2G 32.2				
15	2G 31.5	N 0.0						

N:Fresh Fuel
1:Once Burned Fuel
2:Twice Burned Fuel
NG:Fresh Fuel with Gadolinia
1G:Once Burned Fuel with Gadolinia
2G:Twice Burned Fuel with Gadolinia

—Fuel Types

—Burnup at Beginning of Cycle(GWd/t)

Fig. 1-4 A fuel loading pattern under the multi-batch loading strategy

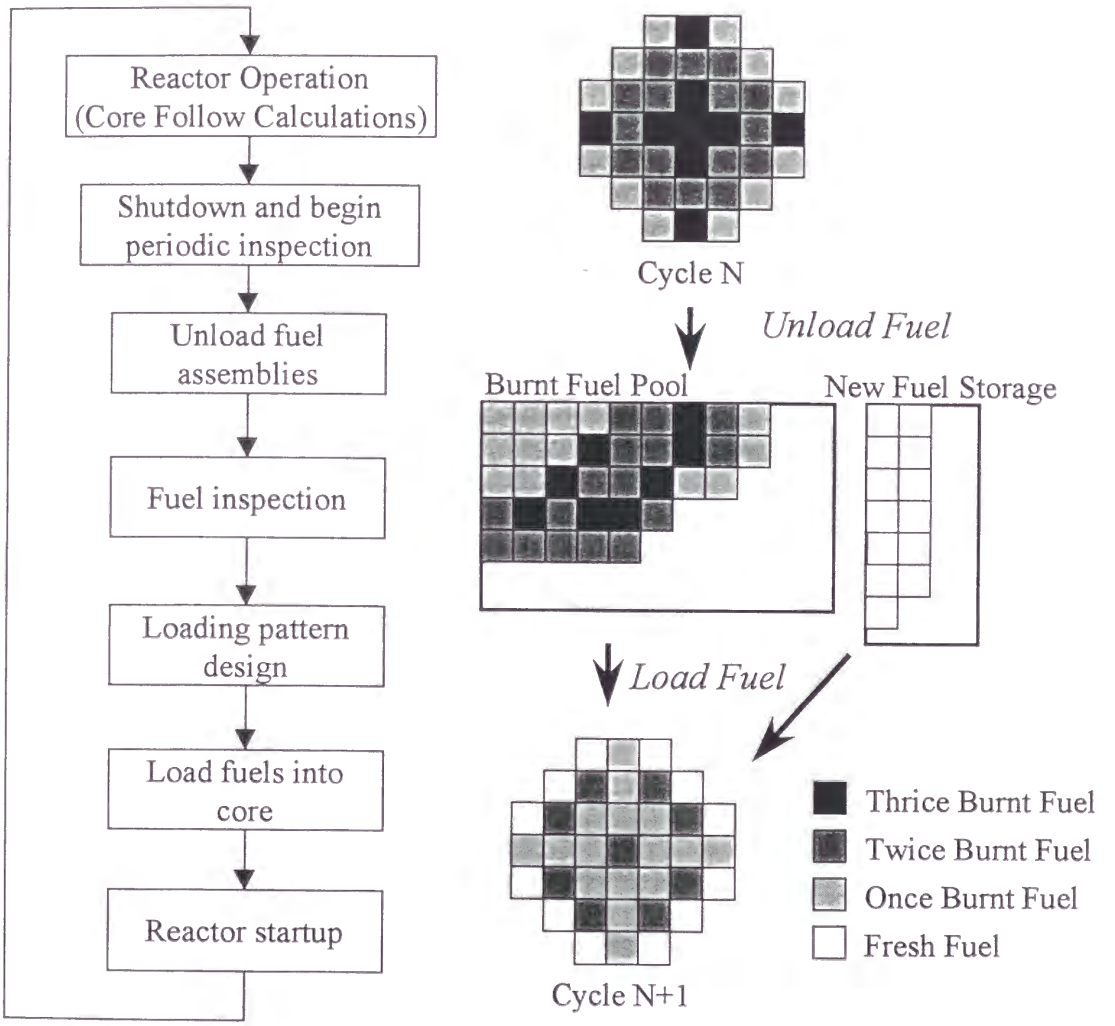


Fig. 1-5 An outline of the reactor operation and the in-core fuel management

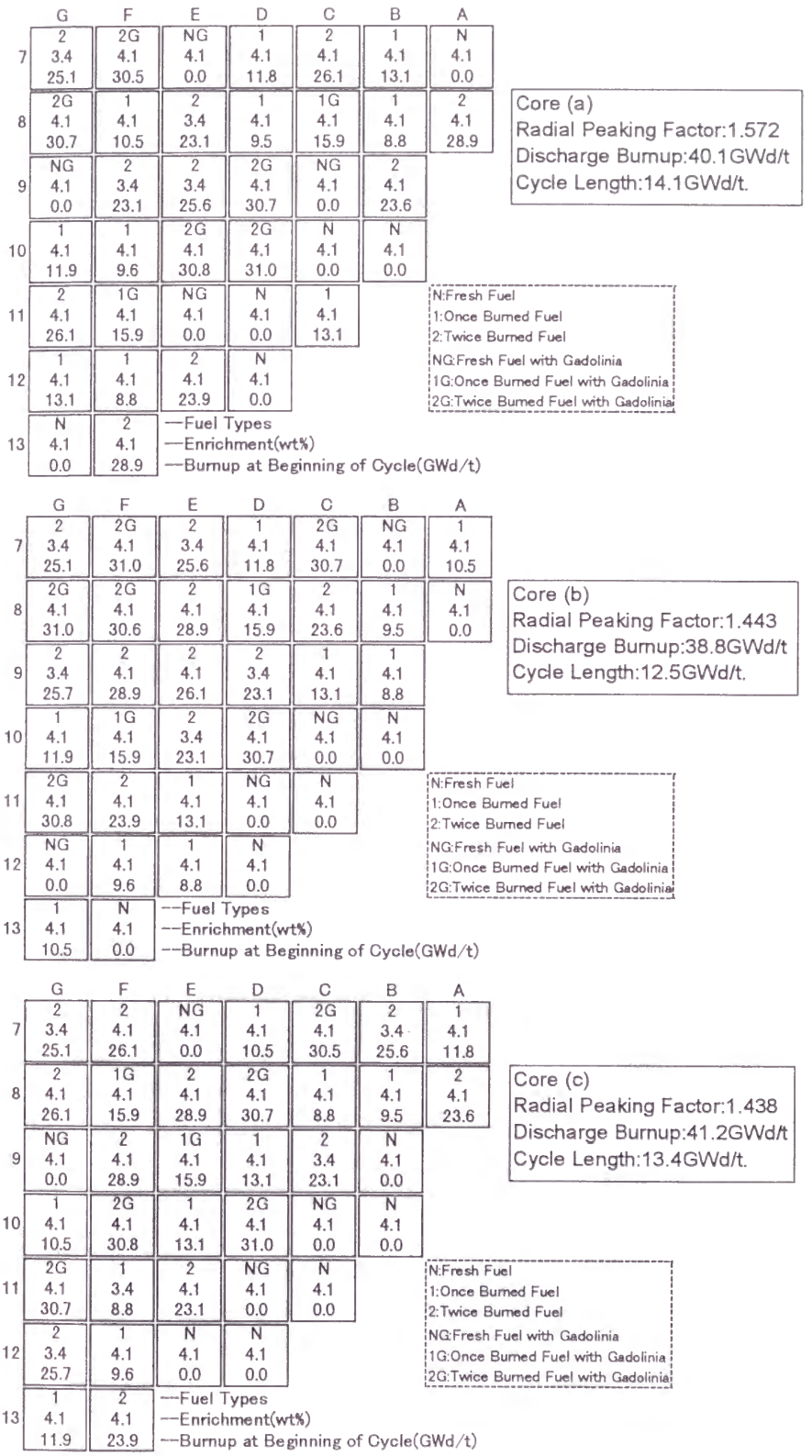


Fig. 1-6 Different PWR cores consisted of same fuel inventory.

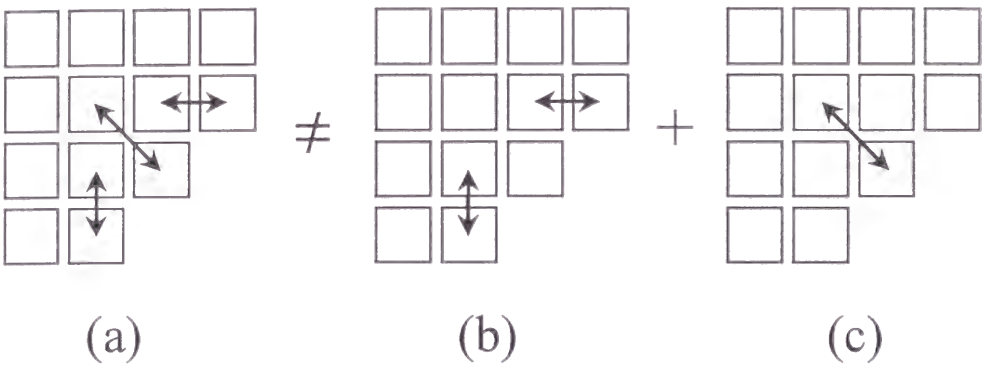


Fig.1-7 Effect of non-linearity on the fuel shuffling

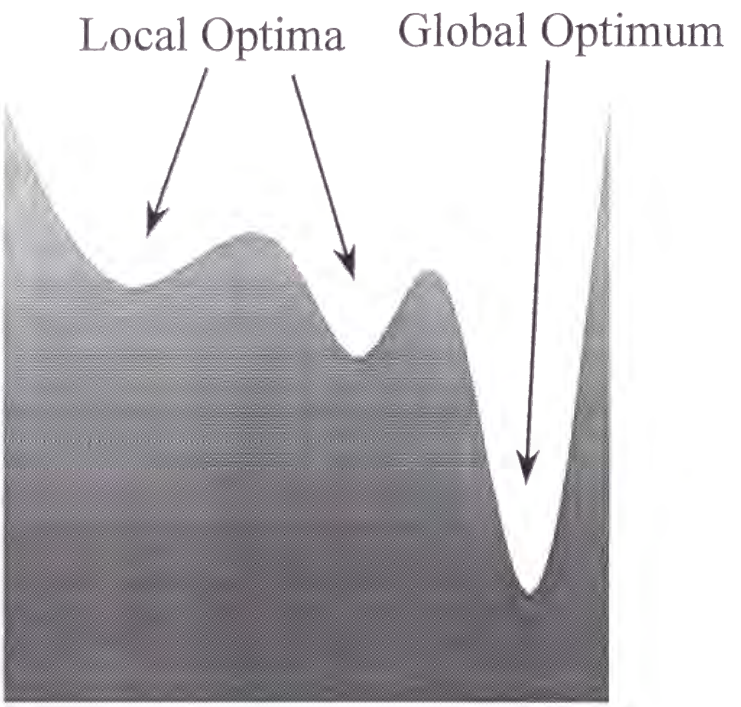


Fig.1-8 Concept of local optima and the global optimum

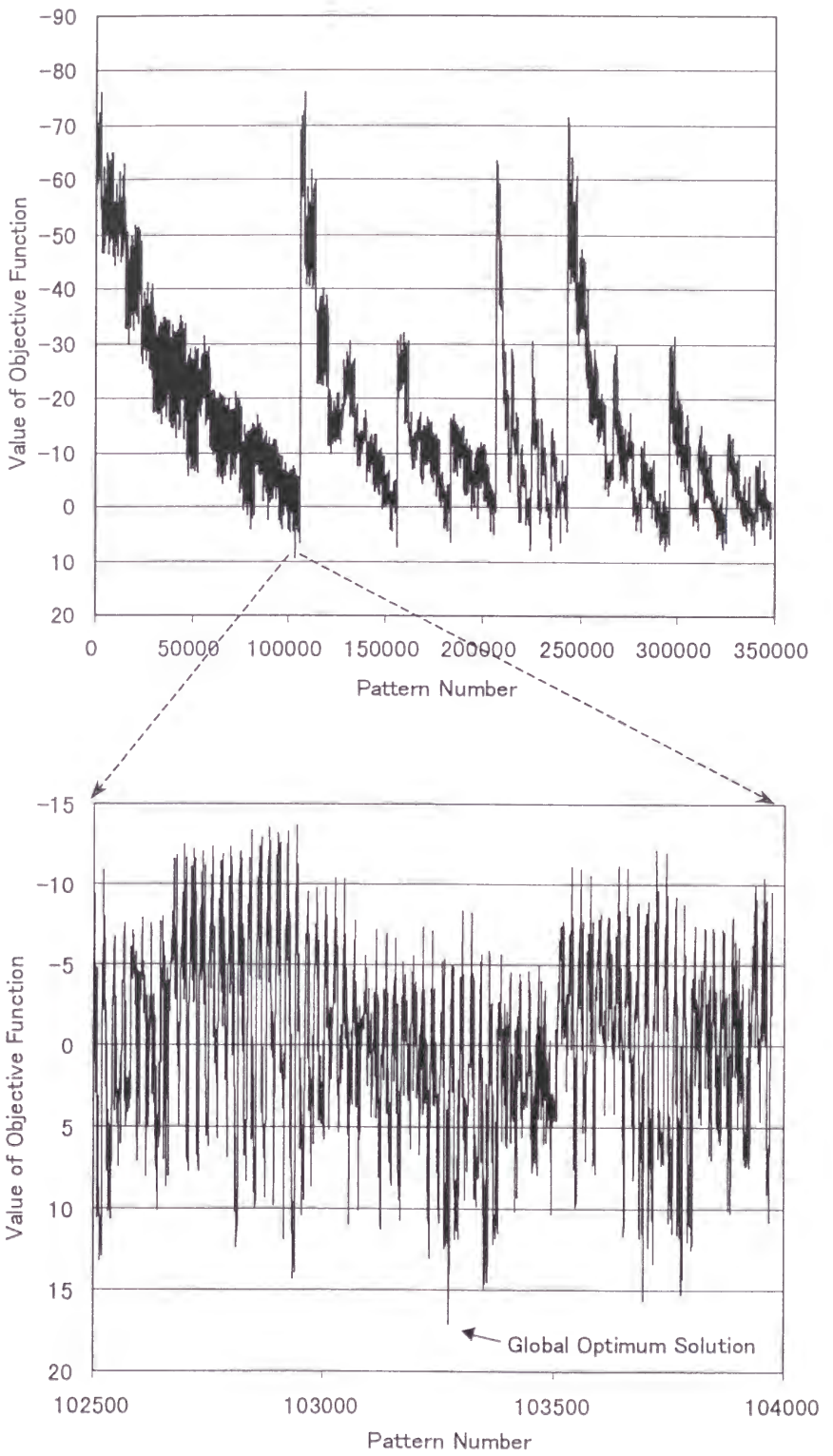


Fig.1-9 Local optima in the actual problem of loading pattern optimization.

CHAPTER 2

A QUANTITATIVE COMPARISON OF LOADING PATTERN OPTIMIZATION METHODS FOR IN-CORE FUEL MANAGEMENT OF PWR

2.1 Introduction

In pressurized water reactors (PWRs), the fuel reloading is periodically performed. The time interval between successive fuel reloadings is currently about one year in Japan. When the fuel reloading is performed, engineers who are responsible for the nuclear core design should execute a reload core analysis to determine the number of fresh, reloaded and/or re-inserted fuel assemblies. They are also responsible for the determination of the loading pattern (LP), which assigns all loading fuel assemblies to unique in-core locations.

In order to improve the neutronics core characteristics of PWR, namely, to improve the economics while satisfying the safety constraints such as the radial power peaking factor, the assembly maximum burnup, the moderator temperature coefficient and so on, the LP optimization is quite important. Especially in PWR, the neutronics core characteristics like the power distribution are essentially determined only by its LP, because the control rods are almost fully withdrawn during the reactor operation and the excess reactivity is suppressed by the chemical shim.

The LP optimization is a discrete and combinatorial problem with a huge design space[1]; a typical size of the design space amounts to approximately 10^{20}-10^{30}. This problem also has a non-linear nature and a multi-modality, which are stumbling blocks to straightforward optimization searches in the design space[2]. Hence, the stochastic optimization methods like the simulated annealing (SA) or the genetic algorithms (GA) are

desirable when we need a global or at least a near global optimum solution.

Though the stochastic optimization methods are quite robust against a complex optimization problem with the multi-modality, these methods usually require a long computation time. Hence, more simple deterministic methods such as the hill climb method, which requires less computational resources, are also considered to be options in the LP optimization.

In the past few decades, various LP optimization methods were developed[1],[3]-[9]. Unfortunately, since these methods were almost independently investigated, it was quite difficult to make a quantitative comparison among these methods. Therefore, a quantitative comparison of the LP optimization performance is considered to be necessary to reveal the superiority and inferiority of these methods. Moreover, hybrid search strategies, which combine two different optimization methods, were not investigated though the hybrid search strategies had the capability to overcome the weaknesses of the independent optimization methods.

In this chapter, the LP optimization performances of the stochastic and the deterministic search methods are quantitatively compared with each other. Furthermore, a hybrid search strategy that combines different optimization methods is newly proposed. The performance of two different hybrid methods, which combine DS with BE and GA with BE, are examined and compared with the performances of the independent optimization methods.

In the section 2.2, the stochastic and deterministic optimization methods treated in this chapter are briefly described. In the section 2.3, the calculated results of the PWR LP optimization benchmark problem are shown. In the section 2.4, these results are summarized and recommendations for LP optimization methods are described.

2.2 Optimization Methods

2.2.1 Simulated Annealing Method

SA is an optimization method whose origin is the simulation of the crystal vibration in annealing metal[6],[7],[10],[11]. When a melting metal is annealed slowly, the energy state of a crystal in the solid metal becomes lower than that of quickly annealed metal. Though the basic concept of SA is the hill climb method which only accepts a higher fitness solution than the current one, a probabilistic state transition to a worse direction in the design space is allowed to escape from local optima.

For example, if one finds a solution X_{i+1} when searching the neighborhood of a solution X_i, and if the evaluated fitness value of solution X_{i+1} is higher than that of X_i, X_{i+1} is adopted and the search continues around the neighborhood of X_{i+1}. On the other hand, if the evaluated fitness value of solution X_{i+1} is lower than that of X_i, X_{i+1} is threw into a trashcan in the simple hill climb method. On the other hand, the solution X_{i+1} has a chance to survive in SA. The probability of survival is defined as follows:

$$\exp(-\delta C / T), \tag{1}$$

where,

δC: difference in evaluated fitness value between X_i and X_{i+1},

T: "temperature" of the system.

When the SA optimization starts, T is set to a large value like a real metal annealing. If T is large enough, the acceptance probability of solutions is almost unity, which means a random search. As the SA optimization search progresses, T becomes lower and lower. As T becomes lower, the acceptance probability of a poor solution becomes smaller.

That is to say, due to the large acceptance probability for the poor solutions, SA

rforms a global search and a solution is not trapped in the local optima in the primary age of optimization. In the latter stage, SA performs a fine local search because SA almost ways rejects a solution that has a worse fitness value than the current base solution.

Like a real metal annealing, the cooling schedule of the system temperature T has a rge effect on the quality of the final solution. When the temperature decreases slowly, mely, using a slow annealing schedule, the required computation time becomes very long. owever, the quality of the final solution will be high. For a quick annealing schedule, the ality of the final solution will be low though the computation time becomes short.

SA has been applied to the LP optimization as follows;

) Assume an initial LP.

) Execute the core burnup calculation using a core calculation code and evaluate the fitness of LP.

) Generate a candidate LP from the initial (or base) LP by random shuffles of the fuel assemblies. Shuffles of binary or ternary assemblies are performed once or twice.

) Estimate the fitness value of the candidate LP generated through the core burnup calculation.

) When the fitness of the candidate LP is higher than that of the base LP, the candidate LP is adopted as the base LP.

) When the fitness of the candidate LP is lower than that of the base LP, the candidate LP is accepted with a probability of $\exp(-\delta C / T)$.

) Repeat the procedures from (3) to (6). The number of repetitions is called as the Malkov length.

) The system temperature is decreased according to the following equation;

$$T^{n+1} = \alpha T^{n}, \qquad (2)$$

where n represents the number of stages or generations and α is the annealing factor, which is smaller than 1.0. When α is chosen to be closer to 1.0, the system temperature decreases more slowly.

(9) Return to (3) until the system temperature reaches low enough and the frequency of change in the base LP is less than a certain value.

2.2.2 Direct Search Method

The direct search (DS) method[3]-[5] has almost the same procedure as SA. The difference between SA and DS is the acceptance criteria of a poor LP. As described previously, SA can accept an LP whose fitness value is lower than that of the base LP. However, in DS, an LP that has a lower fitness value than the base LP is always rejected. In other words, the procedure in DS is equivalent to SA when a system temperature T nearly equals zero.

Therefore, DS takes a less computation time than SA. However, DS cannot escape from the local optima, because DS has no capability to treat the multi-modality in the design space.

2.2.3 Binary Exchange Method

This method is one of the deterministic methods in the LP optimization. The procedures of BE are as follows;

(1) Assume an initial LP.

(2) Execute all possible binary exchanges from the initial (or base) LP and estimate the fitness values of these LPs using a core calculation code.

(3) Perform the best binary exchange which improves the fitness value most effectively. The generated LP is used as the base LP in the next step.

(4) Repeat (2) and (3) until it converges to the best LP.

Since BE tries to perform all possible fuel shufflings, the fuel shuffling is restricted to the binary exchange. If the ternary fuel shuffling is allowed, the number of possible fuel shufflings will become quite large.

In BE, the final best LP is at least guaranteed as a local optimum within a binary exchange of the assemblies; the final LP cannot be improved anymore by a binary exchange of the assemblies. Because SA or DS does not perform exhaustive binary assembly shuffles, the final LP of these optimization methods is not always a local or global optimum. Like DS, BE has no capability to treat the multi-modality in the design space, and hence it cannot escape from the local optima. However, the granularity of the local search by BE is the finest among LP optimization methods. In other words, BE can perform the finest local search in the LP design space.

2.2.4 Genetic Algorithms Method

GA is one of the optimization methods and its concept is based on the genetics and natural selection of life[8],[9],[12]. Namely, a candidate for the solution is represented by a digital chromosome which has enough information to reproduce the original solution.

A population (or generation) of chromosomes is generated, and the fitness values of each chromosome is evaluated. Simulating the Darwinian theory, chromosomes which have lower fitness values will be terminated while superior chromosomes produce their offspring through the genetic operations like the crossover and/or the random mutation. If these procedures are repeated during many generations, the evolution of chromosomes will provide the solutions with higher fitness values.

An evolutionary strategy through the crossover is based on the building block

hypothesis. It insists that a fragment of the chromosome preserves a part of the original nature, and the combination of the fragments from the superior chromosomes has a large possibility to make an outstanding one. Hence, a chromosome should accurately represent the original nature of the solution. In the LP optimization, an ideal two-dimensional chromosome is adopted because the neutronics effects from adjacent fuel assemblies are quite important.

Figure 2-1 shows an example of the ideal two-dimensional chromosome. In the chromosome, the fuel assemblies are labeled in accordance with reactivity ranks in the core. Using this chromosome, genetic operations such as the crossover and/or the random mutations are performed. As a result of the crossover operation, identical reactivity ranks often appear in two different locations on the chromosome. This kind of chromosome means that a single assembly exists in the two different positions at the core. This situation cannot occur in the fuel loading pattern. In such a case, small random numbers are added to the identical ranks to make a small difference between them, and re-ranked as shown in Fig.2-2.

In the mutation operation, two different reactivity ranks (namely, fuel assemblies) are randomly selected from the chromosome and the binary shuffle is performed.

The procedures of LP optimization using GA are as follows;

(1) Generate random initial LPs (initial population) using a pre-defined set of loading fuel assemblies and burnable poisons.
(2) Perform a core calculation for each LP using a neutronics calculation code and evaluate the fitness of each LP.
(3) Select parent patterns according to the evaluated fitness, and perform the genetic operations such as the crossover and the random mutations to make an offspring.

(4) Repeat (2) and (3) until the difference among candidates of the best LP in the populations becomes smaller. In other words, repeat (2) and (3) until the GA search converges.

As described previously, the search logic of DS is the assembly shuffling, which corresponds to the mutation operator in GA. Therefore, if the genetic operator of GA is restricted to only the mutation, the search performance of GA is expected to be almost the same as that of DS. Because the interpretation of a crossover operator in GA is "interpolation" between two different parent chromosomes, the search area in the design space by GA is larger than those of SA, DS and BE. Note that SA, DS and BE generate a next candidate LP by assembly shuffles, and therefore the perturbation scaling is usually smaller than that of GA. On the other hand, the crossover operator is not very good for the local fine search because of its large perturbation scaling.

2.2.5 Hybrid Search Method

In the previous sections, 4 optimization methods were briefly described. These methods have tradeoffs in the aspects of the computation time, the robustness against the multi-modality, the global search capability, the local search capability, and so on. Hence, a hybrid search algorithm which combines the optimization methods is expected to overcome the weakness of each optimization method and improve the quality of the final solution without significant increase in computation time.

In this study, two different hybrid search methods were tried. The first one combined DS with BE (DS+BE), namely, BE was executed using the best LP obtained by DS as an initial LP. The second one combined GA with BE (GA+BE), namely, BE was executed using

the best LP obtained by GA as an initial LP.

SA combined with BE (SA+BE) is considered to be another option. However, DS+BE was used in the present study. Because SA and DS use the same fuel shuffling algorithms, the granularity of the final solution is almost the same. Hence the improvement of solution obtained by the additional BE optimization will be the same both in DS+BE and SA+BE. Since SA takes much computation time, DS+BE was used to estimate the improvement by the hybrid strategy instead of SA+BE.

Note that DS and BE are the candidates of the local search methods for the hybrid search strategy. BE can perform a finer local search than DS, and generally, the computation time of BE is shorter than that of DS. Since the solution from the global search method (SA or GA) almost converges at a near optimum solution, the local fine search method is more suitable for the latter part of the hybrid strategy. Therefore, BE was used for the hybrid search methods in this study.

2.3 Calculations

2.3.1 Benchmark Problem

In order to perform a quantitative comparison among several optimization methods, a single cycle LP optimization benchmark problem was set up. The target reactor was a Westinghouse type 900 MWe 3 loop PWR loaded with 17x17 fuel assemblies. The number of fuel assemblies in the core was 157.

The specification of fuel assemblies used in this benchmark problem is tabulated in Table 2-1. The numbers of fresh, once and twice burned fuel assemblies were 60, 60 and 37, respectively. Gadolinia(Gd) bearing fuel assemblies were used instead of burnable poison rods. An example of LP is shown in Fig. 2-3.

For simplicity, the restrictions on LPs were assumed as follows;

(1) Keep an octant core symmetry.

(2) Assume a uniform burnup distribution inside the assembly.

(3) Fresh fuel assemblies without Gd can be inserted only in the positions P1 and P2 in Fig. 2-3.

(4) Fresh fuel assemblies with Gd cannot be inserted in the position P1 in Fig.2-3.

The fitness function was defined as follows;

$$\text{Fitness}=(\text{Calculated Cycle Length、GWd/t}) - 100\times\text{MAX}[0、(\text{Calculated Fxyn}-1.435)]、 \quad (3)$$

where Fxyn is the maximum radial peaking factor throughout the cycle.

This fitness function is based on the penalty function; it aims to maximize the cycle length while satisfying Fxyn less than 1.435. Though this fitness function is too simple to use in the practical applications, it is considered to be enough to assess the optimization performance of the different methods.

2.3.2 Optimization Calculations

Based on the benchmark problem described in the previous section, several LP optimization calculations were performed to compare the performances of the optimization methods.

In SA, the optimization performance depends on the value of the Malkov length. If the Malkov length is large enough, a true thermal equilibrium state can be realized at an each system temperature during the optimization calculation. This will result in a better solution,

though the computation time becomes longer. For the Malkov length, the value from 50 to 100 was utilized in the LP optimization study so far[13]. Therefore, the Malkov length of 75 was selected in this study.

The optimization performance of SA also depends on the initial system temperature; a high initial system temperature results in a longer computation time, and a low initial system temperature often results in a local optimum solution. In general, the adequate acceptance probability of the worse solution should be approximately 0.7～0.8 at the initial system temperature[7]. Therefore, the initial system temperature was selected to be 10.0 in this study.

The annealing speed of SA is the most important parameter for the optimization performance. In order to investigate the effect of the annealing speed on the quality of the final solution and on the computation time, the annealing parameter, α was set to 0.95, 0.90 and 0.60 in the course of the present study.

The initial LP was always randomly generated using different random seeds. The SA optimization calculation terminated when the best LP chosen in each stage remained the same one during successive five stages (5 stage×75 LPs/stage=375 LPs).

In DS, the search terminated when the best LP remained the same one while estimating 375 LPs. The initial LP was also randomly generated.

In BE, the search terminated when the best LP did not change by any binary exchange of fuel assemblies. The initial LP was also randomly generated.

In GA, 100 LPs were calculated in one generation and the search was performed for 30 generations.

The mutation rate of GA affects the optimization performance. The results obtained by GA with an extremely high mutation rate are almost the same as those obtained by DS as described in Sec. 2.2.4 The mutation operation, however, prevents the pseudo convergence

to the local optima, which comes from the loss of diversity in the population of the chromosomes. In this study, the mutation rate was selected to be 0.1 from the results of preliminary LP optimization calculations. In the preliminary calculations, it was confirmed that the mutation rate did not have a significant impact on the LP optimization performance in the range from 0.05 to 0.3.

In addition to these optimization methods, DS+BE and GA+BE hybrid optimization methods were tried.

The result of optimization might depend on the random seed and on the initial LP used in the calculation. Hence, in order to make a quantitative comparison among these optimization methods, 10 trials were performed in each method using different random seeds. For SA, DS, BE and DS+BE, the initial LP was also changed in each trial. For GA, LPs in the initial population were changed in each trial.

For the core calculation, a two-dimensional coarse mesh(2x2 node/assembly) diffusion calculation, which takes account of the feedback caused by the thermal-hydraulics and includes the boron concentration search, was executed. The radial peaking factor was obtained by the pin power reconstruction method[14].

2.3.3 Results and Discussion

The summary of calculated results are shown in Table 2-2. Table 2-2 contains 8 optimization results including those of the two hybrid optimization methods. Note that the statistical results from the 10 trials are also tabulated in Table 2.

From the fitness values which represent the quality of LP, GA+BE reaches the highest one, and SA(α=0.95), GA, SA(α=0.90), DS+BE, DS, and BE follow GA+BE in this order. GA reaches almost the same fitness value as SA(α=0.90), however, GA+BE reaches a higher fitness value than that of a slow simulated annealing, SA(α=0.95). Since the number of

calculated LPs in SA(α=0.95) is almost three times larger than that in GA+BE, the search performance of GA+BE is considered to be superior than SA for this benchmark problem. Note that the computation time is almost proportional to the number of calculated LPs.

As described before, GA has an advantage in the global search capability, but does not have an enough capability for the fine local search. In contrast to GA, BE is good for the fine local search though it lacks the global search capability. The GA+BE hybrid optimization strategy compensates for the weaknesses of these two methods; the global search is performed by GA, and the local search is subsequently executed by BE.

In DS+BE, however, the value of the fitness function was the same as that of DS only. In other words, improvement in the quality of the solution by BE was not observed in DS+BE. Because DS searches for an optimum solution based on the fuel assembly shuffling, the perturbation scaling or the search granularity is almost the same as that of BE. Therefore, the DS+BE hybrid optimization did not work well. The situation of SA+BE hybrid approach is considered to be almost similar to that of DS+BE, because the search by SA is exactly the same as DS when the system temperature T becomes low enough.

Standard deviations of the fitness values also include important information about the quality of the solution. Because the standard deviation of fitness value is considered to indicate the dependence on the random seed, a small standard deviation is desirable. SA(α=0.95) has the smallest standard deviation among the 8 optimization methods, and SA(α=0.90), GA+BE, GA, DS, DS+BE, SA(α=0.60), and BE follow in this order. The standard deviations of BE, DS and DS+BE are large, because these methods have no capability to escape from local optima. SA(α=0.60) also has a large standard deviation, because the annealing speed is too rapid to escape from the local optima.

The standard deviation of GA is slightly larger than that of SA(α=0.95) or SA(α=0.90). Since the maximum fitness value of GA among 10 trials is larger than that of SA, GA is

considered to search a more global area than SA(α=0.95). One of the reasons for the large standard deviation comes from the local search capability of GA. Since the local search capability of GA is inferior to that of the other optimization methods, the standard deviation of the fitness value becomes large. In addition, the LP design space structure is quite complex[2], hence the standard deviation of the fitness values may become larger as the search area increases[15]. From the above reasons, the standard deviation of GA was considered to become larger than that of SA. This result also shows that when the annealing speed is slow enough, SA provides a less random seed and less initial LP dependent solutions.

GA+BE has smaller standard deviation than GA only. This fact indicates that the local search by BE executed subsequently to the global search by GA results in more consistent solutions. In other words, GA+BE less depends on a seed of the initial random number.

Figure 2-4 shows fitness values by GA+BE and SA(α=0.95) in the course of optimization calculations. Figure 2-5 shows the breakdown of the fitness values, namely, the calculated results of the cycle length and Fxyn by GA+BE and SA(α=0.95). Note that these results are the average of 10 trials. From Fig. 2-4, one can observe that the fitness value by GA+BE increases faster than that by SA(α=0.95). This is because GA+BE improves the cycle length more quickly than SA(α=0.95) as shown in Fig. 2-5. The fitness value of GA+BE significantly increases in the latter stage of calculation whereas that of SA(α=0.95) calculation saturates in the latter stage and does not improve anymore. In GA+BE, BE significantly improves the fitness value after the search by GA. In SA, however, the same improvement is not expected even if BE is executed as discussed previously.

The LPs of the maximum fitness value, which were obtained by GA+BE and SA(α=0.95), are shown in Fig. 2-6 for reference. For the purpose of increasing the cycle length, both LPs become typical low leakage loading patterns.

In the present study, a typical 3 loop type PWR was selected as the target core. Though the structure of the LP design space depends on the core size and the loaded fuel inventories, the nature of the LP design space will be insensitive to these characteristics. Of course the computation time depends greatly on the core size and the number of fuel assemblies in the core. However, the relative optimization performance of each method is considered to be almost the same in the other core types or fuel inventories.

2.4 Conclusions

In order to perform a quantitative comparison of LP optimization methods, several methods were examined through the PWR optimization benchmark problem. The LP optimization methods based on the assembly binary exchange (BE), the direct search (DS), the simulated annealing (SA), and the genetic algorithms(GA) methods were compared with each other. In addition to these independent optimization methods, the hybrid search strategy which combined different search methods was newly proposed. Two different hybrid search methods which combined DS with BE (DS+BE), and GA with BE (GA+BE) were examined and the performances were quantitatively compared with those of the independent optimization methods.

Among these optimization methods, GA+BE provided the highest average fitness value, which represented the quality of the final LP. Though the slow simulated annealing SA(α=0.95) gave almost the same fitness value as GA+BE, the number of calculated LPs was about three times larger than that of GA+BE.

The GA+BE hybrid search strategy performed the best because the natures of GA and BE are quite different; the global search by GA and the local search by BE compensated for each weakness of GA and BE. On the other hand, the results of DS+BE hybrid search strategy were the same as those of DS only, because the principles of search in these two

methods are very similar.

GA improved the fitness value much faster than SA especially in the primary optimization stage due to the essential difference between the two search methods.

The number of calculated LPs by BE or DS was smaller than that of SA or GA. However, because BE or DS is not robust against the multi-modality, the final solution is usually trapped into local optima and the average of fitness values is significantly lower than that of SA or GA.

Through the present study, the superiority and inferiority of the independent LP optimization methods are clarified. Furthermore, it is demonstrated that the hybrid optimization method (GA+BE) presented in this study is quite effective as the LP optimization method. The GA+BE hybrid optimization method is considered to be applicable to solve not only the LP optimization problems of PWR but also that of other reactor types.

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Table 2-1 Fuel assemblies used in the benchmark calculations

^{235}U Enrichment (wt%)	Burnable Poison	Assembly Burnup (GWd/t)	Number of Fuel Assemblies
4.1	Gd	34.7	1
4.1	Gd	34.7	4
4.1	Gd	32.7	4
4.1	Gd	32.2	4
4.1	---	28.9	4
4.1	---	27.9	8
4.1	---	23.8	8
4.1	---	23.0	4
4.1	Gd	19.5	4
4.1	Gd	19.0	8
4.1	Gd	18.9	8
4.1	Gd	18.4	8
4.1	Gd	16.8	4
4.1	Gd	16.8	4
4.1	---	12.6	4
4.1	---	12.6	4
4.1	---	11.3	8
4.1	---	10.2	8
4.1	Gd	0.0	4
4.1	Gd	0.0	8
4.1	Gd	0.0	8
4.1	Gd	0.0	8
4.1	Gd	0.0	8
4.1	---	0.0	8
4.1	---	0.0	8
4.1	---	0.0	8

Table 2-2 Summary of calculated results for the optimization benchmark (10 trials in each method)

Method*	Initial Temp.	α	Fxyn		Cycle Length(GWd/t)		Fitness Value			Number of Calculated LPs	
			Average	Std.Dev.	Average	Std.Dev.	Average	Maximum	Std.Dev.	Average	Std.Dev.
BE	---	---	1.4570	0.0224	17.350	0.297	15.111	17.173	2.005	297	52
DS	---	---	1.4372	0.0088	17.200	0.394	16.808	17.498	0.680	1268	455
DS+BE	---	---	1.4372	0.0088	17.200	0.394	16.808	17.498	0.680	1317	455
SA	10	0.60	1.4341	0.0130	17.224	0.241	16.805	17.346	0.997	1583	423
SA	10	0.90	1.4310	0.0045	17.280	0.171	17.263	17.539	0.152	5333	981
SA	10	0.95	1.4315	0.0035	17.343	0.138	17.343	17.524	0.138	10313	1319
GA	---	---	1.4302	0.0096	17.266	0.187	17.265	17.656	0.187	3000	0
GA+BE	---	---	1.4318	0.0021	17.389	0.179	17.389	17.786	0.179	3509	187

* BE : Binary Exchange, DS : Direct Search, SA : Simulated Annealing, GA : Genetic Algorithms

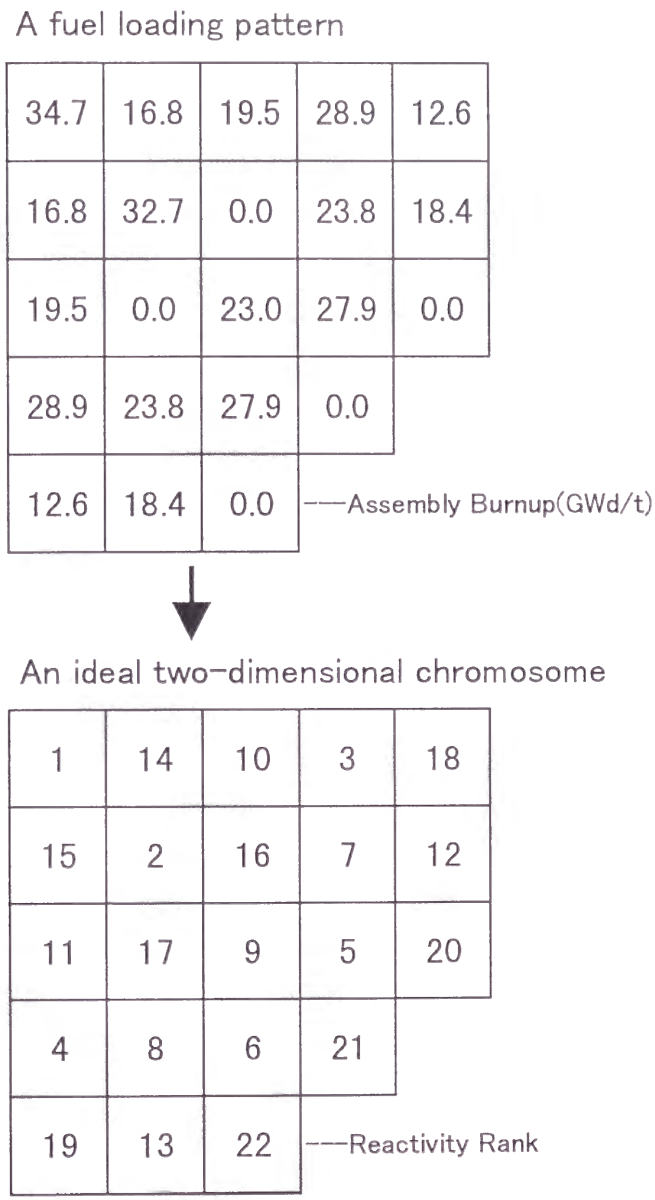

Fig. 2-1 A fuel loading pattern and a corresponding two-dimensional chromosome of an ideal small core.

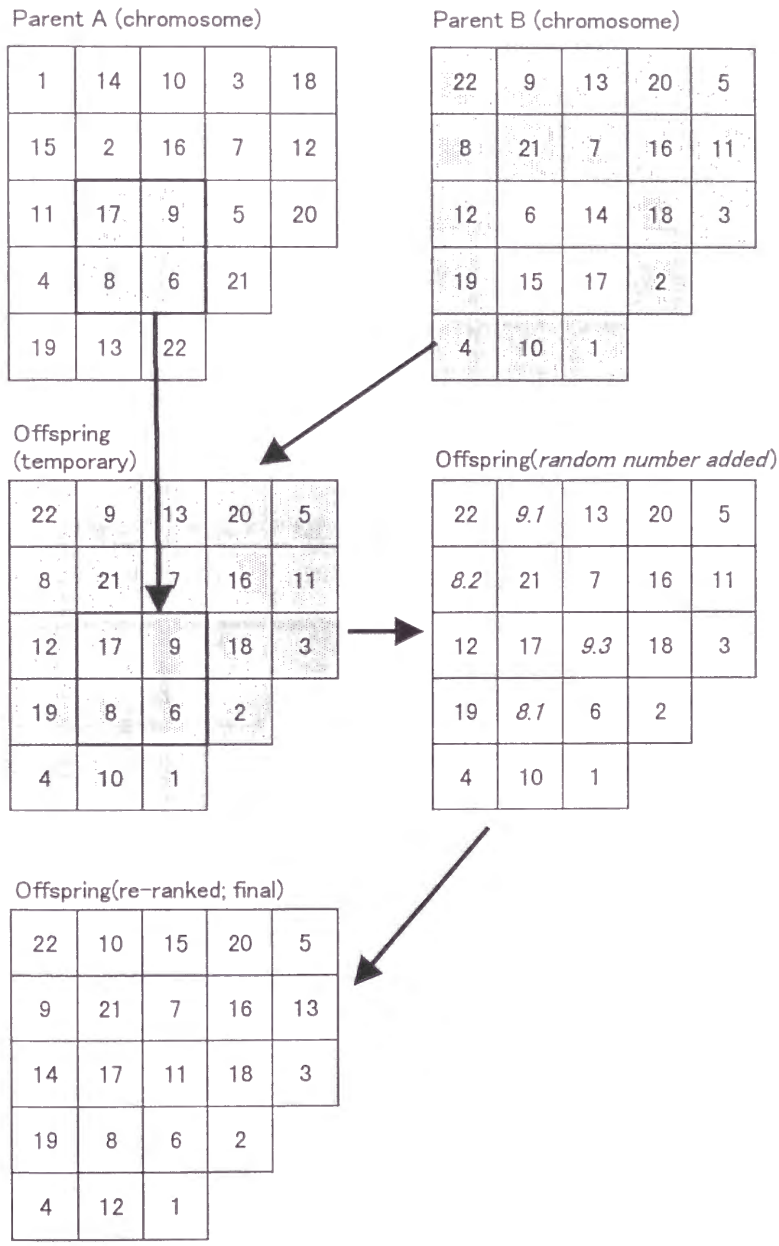

Fig.2-2 An example of the crossover operation using the two-dimensional chromosomes of the fuel loading pattern.

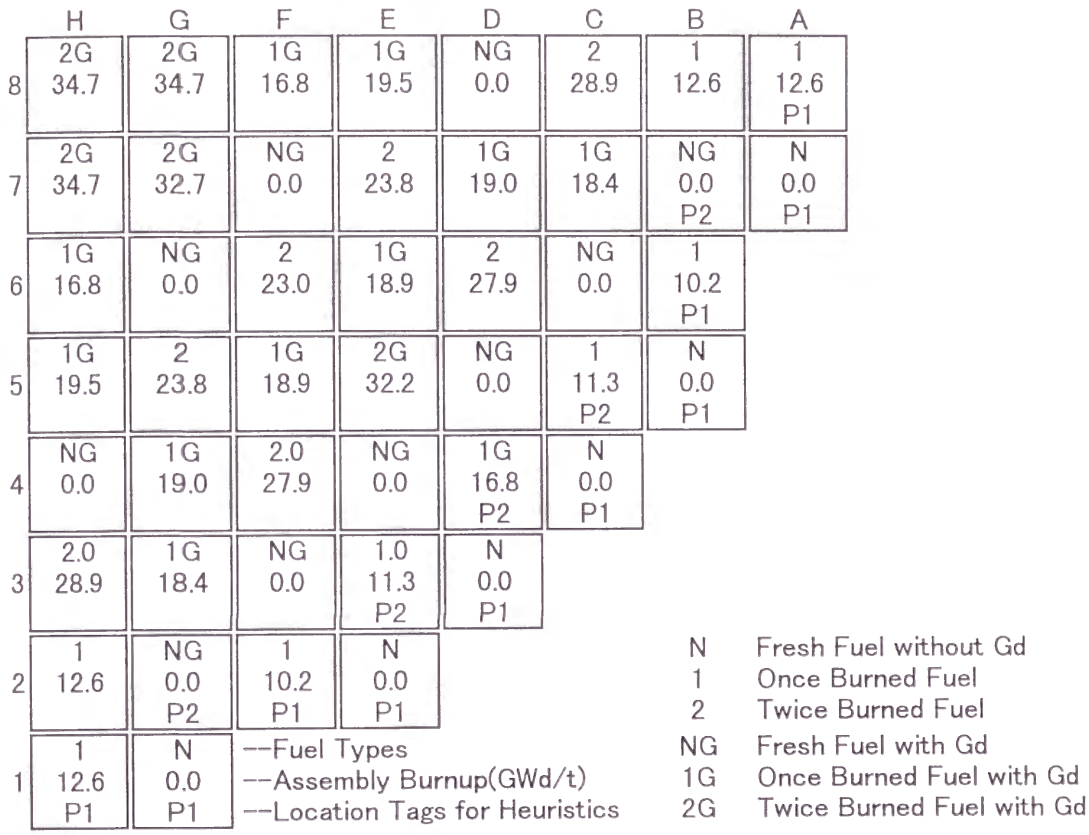

Fig.2-3 An example of the fuel loading pattern in the benchmark problem.

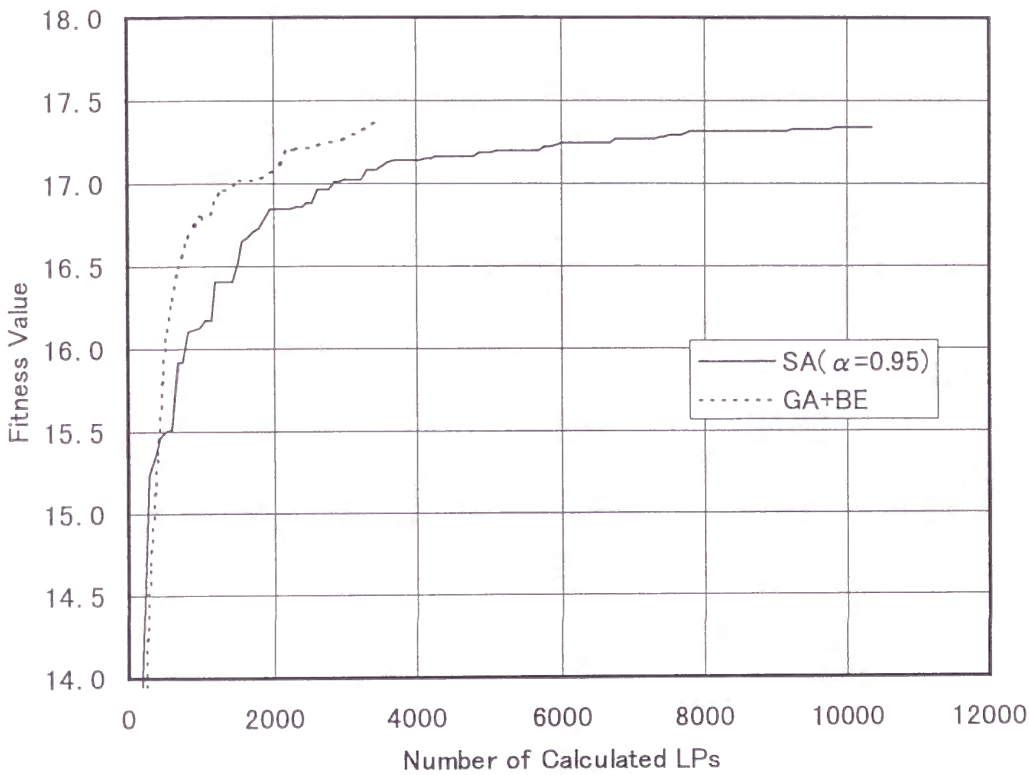

Fig.2-4 Comparison of the fitness values calculated by SA(α=0.95) and GA+BE. (average of 10 trials for each method)

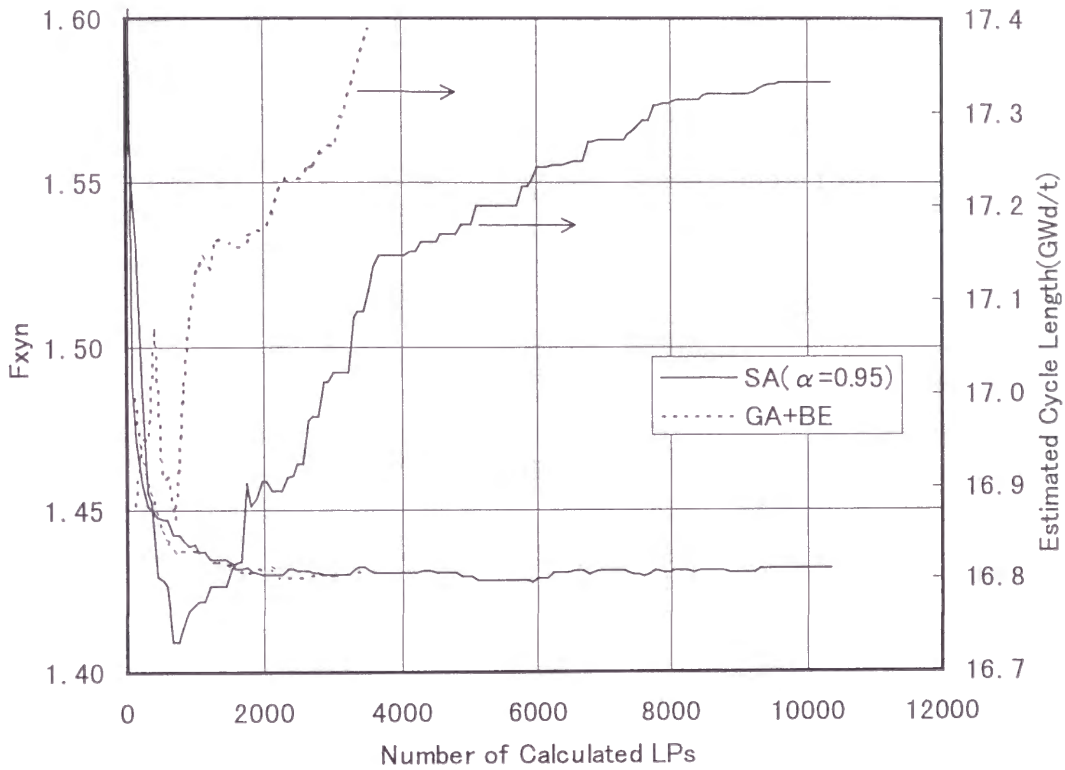

Fig.2-5 Comparison of Fxyn and the cycle length calculated by SA(α=0.95) and GA+BE. (average of 10 trials for each method)

	H	G	F	E	D	C	B	A
8	2G 34.7	2G 32.7	1 12.6	2 28.9	1G 19.5	1G 16.8	NG 0.0	2G 34.7 P1
7	2G 32.7	1 12.6	NG 0.0	2 27.9	NG 0.0	1G 19.0	N 0.0 P2	2 23.8 P1
6	1 12.6	NG 0.0	1 23.0	1 11.3	1G 18.9	NG 0.0	1G 18.4 P1	
5	2 28.9	2 27.9	1 11.3	2G 32.2	NG 0.0	1 10.2 P2	N 0.0 P1	
4	1G 19.5	NG 0.0	1G 18.9	NG 0.0	1G 16.8 P2	N 0.0 P1		
3	1G 16.8	1G 19.0	NG 0.0	1 10.2 P2	N 0.0 P1			
2	NG 0.0	N 0.0 P2	1G 18.4 P1	N 0.0 P1				
1	2G 34.7 P1	2 23.8 P1						

--Fuel Types
--Assembly Burnup(GWd/t)
--Location Tag for Heuristics

N	Fresh Fuel without Gd
1	Once Burned Fuel
2	Twice Burned Fuel
NG	Fresh Fuel with Gd
1G	Once Burned Fuel with Gd
2G	Twice Burned Fuel with Gd

Fig.2-6(a) Best LPs calculated by SA(α=0.95) in the benchmark problem

	H	G	F	E	D	C	B	A
8	2G 34.7	2G 32.7	1G 16.8	2G 32.2	2 28.9	1 12.6	NG 0.0	2 23.0 P1
7	2G 32.7	1G 19.5	NG 0.0	1 11.3	NG 0.0	1G 18.4	1 10.2 P2	N 0.0 P1
6	1G 16.8	NG 0.0	1G 16.8	1G 18.9	2 23.8	NG 0.0	N 0.0 P1	
5	2G 32.2	1 11.3	1G 18.9	1 12.6	NG 0.0	N 0.0 P2	1G 19.0 P1	
4	2 28.9	NG 0.0	2 23.8	NG 0.0	2G 34.7 P2	2 27.9 P1		
3	1 12.6	1G 18.4	NG 0.0	N 0.0 P2	2 27.9 P1			
2	NG 0.0	1 10.2 P2	N 0.0 P1	1G 19.0 P1				
1	2 23.0 P1	N 0.0 P1						

--Fuel Types
--Assembly Burnup(GWd/t)
--Location Tag for Heuristics

N	Fresh Fuel without Gd
1	Once Burned Fuel
2	Twice Burned Fuel
NG	Fresh Fuel with Gd
1G	Once Burned Fuel with Gd
2G	Twice Burned Fuel with Gd

Fig.2-6(b) Best LPs calculated by GA+BE in the benchmark problem

CHAPTER 3

LOADING PATTERN OPTIMIZATION USING HYBRID GENETIC ALGORITHMS

3.1 Introduction

Determination of fuel loading pattern (LP) in a nuclear reactor core has the characteristics of combinatorial optimization problem, because all reloading and fresh fuel assemblies are individually assigned to a unique in-core location. Therefore, to reach a really global optimum solution, complete exhaustive calculations are inevitable in the optimization search. However, a total number of LPs in current commercial reactors is enumerated to an astronomical one.

In addition to this difficulty, an LP optimization problem has a non-linear nature and many local optima that disturb the progress in the optimization search. From a commercial point of view, it is desirable that the determined LP is as economical as possible while satisfying the safety requirements such as the power peaking factor, the maximum assembly burnup, the moderator temperature coefficient, and so on. Therefore, the LP optimization problem can be defined as a multi-objective, multi-constraints combinatorial one.

To solve this kind of problems, it is required to use robust combinatorial optimization techniques. Because the results of deterministic optimization techniques such as the linear programming are often trapped into local optima, stochastic search methods such as the simulated annealing and genetic algorithms (GA) are considered to be suitable[1] [2]. Though the stochastic optimization approach is very computer intensive, it has become feasible as a result of the recent evolution

in powerful computer hardware. Therefore, LP optimization problems are gradually moving from the realm of research to industry[3]-[5].

An LP optimization code for PWRs, GALLOP, was developed on the basis of hybrid GA to automate the generation of LPs and to improve the LP performance. In the present chapter, the features of GALLOP are described first. Then the verification results are shown by applying GALLOP to an optimization benchmark problem for a single cycle. In this well-defined benchmark problem, a true global optimum solution has been known already through exhaustive calculations. Therefore, the optimization capability of the code was evaluated quantitatively.

3.2 Optimization Method

3.2.1 Genetic Algorithms

The genetic algorithms (GA) are a kind of optimization techniques. The basic concept of GA is the evolution of life. In other words, GA searches for an optimum solution by simulating the natural selection of Darwinian theory; crossover and random mutations of chromosomes.

In generally speaking, GA is considered to be suitable for the following type of problems;

(1) Combinatorial or discrete optimization problem with a huge search space and strong multi-modality.
(2) The fitness of each solution can be evaluated, however, the mathematical modeling for the gradient projection is difficult.
(3) A true optimum solution is not necessary, but candidates of the optimum solution are required.

For a long time, GA had remained in the academic area. However, as a result of the recent development in computer technology, GA is beginning to be applied to a wide range of commercial area, such as the optimization of the computer networks, the job scheduling and the structure geometry.

Since the above features are common with the LP optimization problems, it was expected that the application of GA to these problems would be successful.

3.2.2 Application of Genetic Algorithms to Loading Pattern Optimization

When GA is applied to the LP optimization problems, LPs should be represented by chromosomes. To realize a rapid search, the chromosomes employed in GA should accurately represent the nature of the original LP which is the phenotype of the chromosomes. Therefore, two dimensional fuel arrangement of LP are directly used as an ideal two dimensional chromosomes. In this ideal two dimensional chromosomes, fuel assemblies are identified according to their reactivity order[5].

It is considered that GA is suitable for a global search because of it's robustness against the multi-modality. However, a weak point of GA is that one cannot perform a local fine search around an optimum solution. Because GA cannot perform the gradient projection search in the design space, the driving force to find out the fine structure in the design space is small. Sometimes GA reaches to a near optimum solution very quickly. After that, the optimization process stagnates and does not get closer to the optimum any more.

One of the concepts to make a breakthrough at this point is the application of a hybrid search algorithm. At the primary optimization stage, GA is used for the

global search. After GA is used to find a point near an optimum solution, a local search is performed successively. By using hybrid search algorithms, the quality of the solution improves very much without any significant increase in computation time. In the present study, we adopted the local search based on the assembly binary exchange.

3.2.3 Development of the GALLOP code

Using the hybrid GA, an LP optimization code for PWRs, GALLOP, was developed. The sequence of calculations is as follows;

(1)Generate random initial patterns (initial population) using a pre-defined set of loading fuel assemblies and burnable poisons.

(2)Execute the core calculation for each LP using a neutronic analysis code and evaluate the fitness of each LP.

(3)Select the parent patterns according to the above evaluation of fitness, and perform genetic operations such as the crossover or the random mutations to make the offspring.

(4)Repeat (2) and (3) until the difference among candidates of the best LP in successive populations becomes small. In other words, repeat (2) and (3) until the GA search converges.

(5)When the GA search is finished, the local search is subsequently performed using the best LP from GA as an initial LP.

(6)Assembly rotation search follows the local search.

For the core calculation, a two-dimensional coarse mesh(2x2/assembly)

diffusion calculation, which takes account of the feedback caused by the thermal hydraulics behavior and includes the boron concentration search, is executed. The improved coarse mesh method[6] or the analytic nodal method[7] is used to obtain the neutron flux distributions. The radial peaking factor is calculated by using the pin power reconstruction method[8] or by a rough estimation using the intra-assembly power gradient and the local peaking factors. The core calculation code is completely independent from the GALLOP code, and called from GALLOP through a system function.

In the local search, all possible binary exchanges are tried. Therefore, the final solution is at least guaranteed as a local optimum within the Humming length of one. To reduce the computation time, heuristic rules are applied to the offspring. In addition, neural networks[9] will be used for the prediction of power distribution in the core to screen the poor LPs which only satisfy the heuristics.

For the application to commercial fields, not only the search performance, but also the flexibility in the selection of objective functions is important. The GALLOP code can treat many objectives, such as the cycle length, the radial peaking factor, the temperature coefficient, the discharge burnup, the cross radial power tilt, and so on.

3.3 Calculations

3.3.1 Single Cycle Optimization Benchmark

To qualify the optimization capability of the GALLOP code, a benchmark problem was setup. The target reactor was an Westinghouse(WH) type 3 loop PWR, which has 157 assemblies in the core. The benchmark core consisted of 24 fresh fuels without gadlinia(Gd), 36 fresh fuels with Gd, 60 once burned fuels and 37

twice burned fuels. The ^{235}U enrichment of fresh fuel was fixed to be 4.1wt%.

For the optimization benchmark problem, a global optimum solution should be identified. However, the total enumeration number of LPs in an actual commercial reactor is quite huge. Therefore, following assumptions were made to reduce the total enumeration number.

(1) Fresh fuel assemblies without Gd were always loaded at the core periphery as shown in Fig. 3-1.
(2) Fresh fuel assemblies with Gd were always loaded inside the core as shown in Fig. 3-1.
(3) Fresh fuel assemblies with Gd were not arranged adjacent side by side.
(4) Fuel assemblies located at the quarter symmetric positions (indicated by "4" in Fig.3-1) were not exchanged with the fuel assemblies located at the octant symmetric positions (indicated by "8" in Fig.3-1).
(5) The burnup was uniquely 15.5 GWd/t for the once burned fuel assemblies, and 28.3 GWd/t for the twice burned fuel assemblies.

Using these assumptions, the total enumeration number of LPs in the benchmark was reduced to around 350 thousands. Figure 3-2 shows an example of LP in the database.

A complete set of database was generated from the results of exhaustive core calculations. Figure 3-3 shows a histogram of the radial power peaking factor (Fxyn) in the database. When the value of Fxyn is limited to be less than 1.435, the number of feasible LPs is about 150. This corresponds to 0.04% of the total number of LPs in the database. Since the number of feasible LPs is quite few in the database, it is

considered to be suitable as an optimization benchmark problem.

In the present study, the following 4 sets of optimization problems were investigated:

(1) Minimize Fxyn,

(2) Maximize the cycle length,

(3) Maximize the cycle length subject to Fxyn <1.435,

(4) Maximize the cycle length subject to Fxyn <1.435 and the moderator temperature coefficient<-0.5pcm/℃.

The first two problems are the simple optimization without constraint, the last two are the more realistic optimization with constraints. Especially, the last problem includes major constraints in the scoping analysis at the actual commercial reactors.

3.3.2 Results and Discussion

In the calculation by the GALLOP code, 100 LPs were estimated in one generation and it continues during 30 generations. After the GA search has been completed, the local search was performed subsequently. According to the calculated results, the local search was usually converged within 100 LPs.

Because GA uses random numbers, the search by GA depends on the initial random seed. In order to investigate the quantitative optimization performance, the deviation among the final solutions is important. Therefore, 10 trials were performed for each problem.

A summary of calculated results by the GALLOP code is shown in Fig. 3-4. The detail results of calculations for the all problems are shown in from Tables 3-1 to 3-4. In these figures or tables, a rank of optimized pattern corresponds to the position of the final solution (final LP) in the exhaustive database; for example, the rank 1 corresponds to a global optimum solution in the database.

For the all problems, more than a half of results obtained by the GALLOP code reached a global optimum solution. Especially, all of the results reached a global optimum solution for the problems (1) and (2). For the problem (3), 3 among 10 results reached the rank 2 solution, but the difference between the rank 1 and the rank 2 is quite small. We can see almost the same results in the problem (4).

Figure 3-5 shows the probability to obtain a true optimum solution when LPs are randomly generated. When approximately 3000 LPs are randomly generated, the probability to obtain the optimum solution is less than 1%. Therefore, it can be concluded that the search by GALLOP is quite effective.

Through these benchmark calculations, it is considered that the powerful optimization capability of GALLOP was demonstrated.

3.4 Conclusions

The optimization code of loading patterns, GALLOP, was developed for the in-core fuel management of PWRs. The GALLOP code uses the hybrid GA, which combines the global search by GA and the local search by the binary exchange, and has a capability to treat many objective functions. The capability of the GALLOP code was confirmed through well-defined benchmark problems for a single cycle.

In the benchmark problem for the single cycle optimization, the GALLOP code can find out the global optimum solution under several constraints such as the

radial peaking factor, the cycle length, moderator temperature coefficient, and so on. This fact indicates a robust search capability of the GALLOP code.

From these results, it is concluded that the GALLOP code is useful not only in the academic optimization research, but also in industrial applications.

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Table 3-1 Detail results of calculations for the problem (1) in the single cycle optimization benchmark problems.

Trials	Fxyn	Cycle Length(GWd/t)	Moderator Temp. Coef. (pcm/℃)	Reaching Final Pattern at	Rank of Optimized Patterns
1	1.3665	16.911	-	2100	1
2	1.3665	16.911	-	2500	1
3	1.3665	16.911	-	2100	1
4	1.3665	16.911	-	2100	1
5	1.3665	16.911	-	1300	1
6	1.3665	16.911	-	2100	1
7	1.3665	16.911	-	1900	1
8	1.3665	16.911	-	3040	1
9	1.3665	16.911	-	1100	1
10	1.3665	16.911	-	2300	1
Average	1.3665	16.911	-	2054.0	1.0
Std.Dev.	0.0000	0.000	-	523.7	0.0

Table 3-2 Detail results of calculations for the problem (2) in the single cycle optimization benchmark problems.

Trials	Fxyn	Cycle Length(GWd/t)	Moderator Temp. Coef. (pcm/℃)	Reaching Final Pattern at	Rank of Optimized Patterns
1	1.6827	17.611	-	3041	1
2	1.6827	17.611	-	3041	1
3	1.6827	17.611	-	3040	1
4	1.6827	17.611	-	3042	1
5	1.6827	17.611	-	3041	1
6	1.6827	17.611	-	2500	1
7	1.6827	17.611	-	2900	1
8	1.6827	17.611	-	3040	1
9	1.6827	17.611	-	3041	1
10	1.6827	17.611	-	3040	1
Average	1.6827	17.611	-	2972.6	1.0
Std.Dev.	0.0000	0.000	-	163.0	0.0

Table 3-3 Detail results of calculations for the problem (3) in the single cycle optimization benchmark problems.

Trials	Fxyn	Cycle Length(GWd/t)	Moderator Temp. Coef. (pcm/°C)	Reaching Final Pattern at	Rank of Optimized Patterns
1	1.4336	17.144	-	3042	1
2	1.4336	17.144	-	800	1
3	1.4336	17.144	-	3043	1
4	1.4336	17.144	-	3045	1
5	1.4335	17.133	-	1500	2
6	1.4335	17.133	-	1900	2
7	1.4336	17.144	-	3042	1
8	1.4336	17.144	-	3042	1
9	1.4336	17.144	-	3127	1
10	1.4335	17.133	-	2000	2
Average	1.4336	17.141	-	2454.1	1.3
Std.Dev.	0.0000	0.005	-	796.6	0.5

Table 3-4 Detail results of calculations for the problem (4) in the single cycle optimization benchmark problems.

Trials	Fxyn	Cycle Length(GWd/t)	Moderator Temp. Coef. (pcm/°C)	Reaching Final Pattern at	Rank of Optimized Patterns
1	1.4249	17.133	-0.56	3044	1
2	1.4249	17.133	-0.56	1800	1
3	1.4314	17.111	-0.55	1400	2
4	1.4314	17.111	-0.55	3000	2
5	1.4291	17.033	-0.56	3041	5
6	1.4249	17.133	-0.56	1700	1
7	1.4249	17.133	-0.56	1600	1
8	1.4291	17.033	-0.56	3127	5
9	1.4249	17.133	-0.56	1400	1
10	1.4314	17.111	-0.55	3044	2
Average	1.4277	17.107	-0.56	2315.6	2.1
Std.Dev.	0.0029	0.038	0.00	744.8	1.5

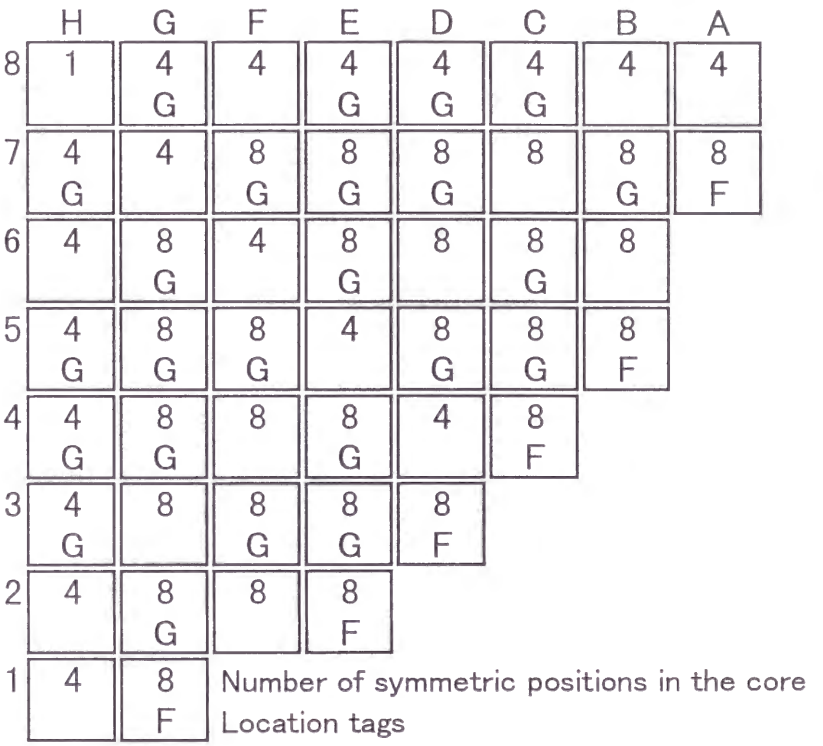

Fig. 3-1 The number of symmetric positions in the core and the location tags in single cycle optimization benchmark problem. Fresh fuel without Gd can be placed at the location indexed by "F". Fresh fuel with Gd can be placed in the location indexed by "G".

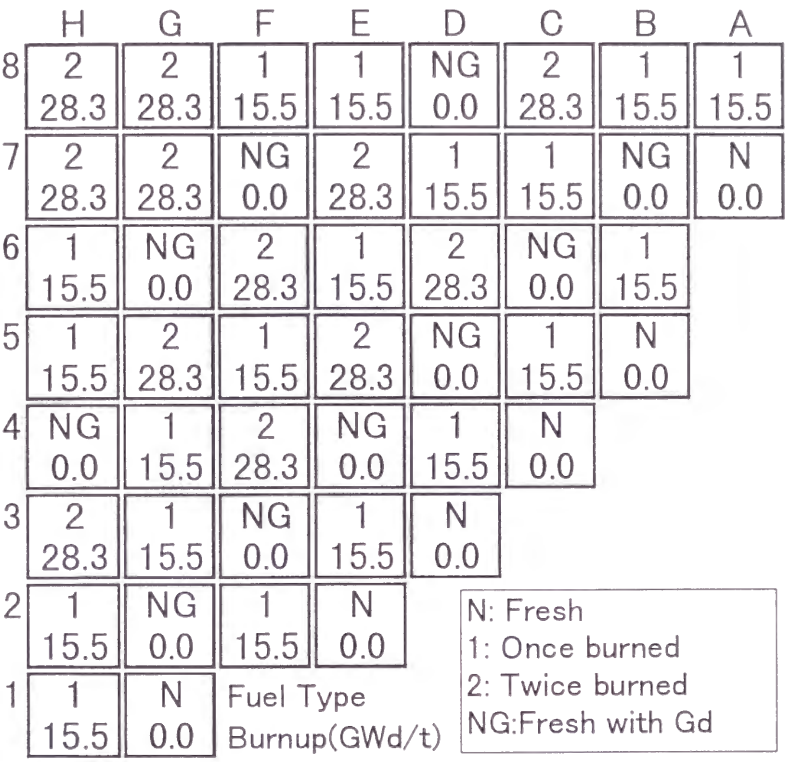

Fig. 3-2 Example of the loading pattern used in the single cycle optimization benchmark problem.

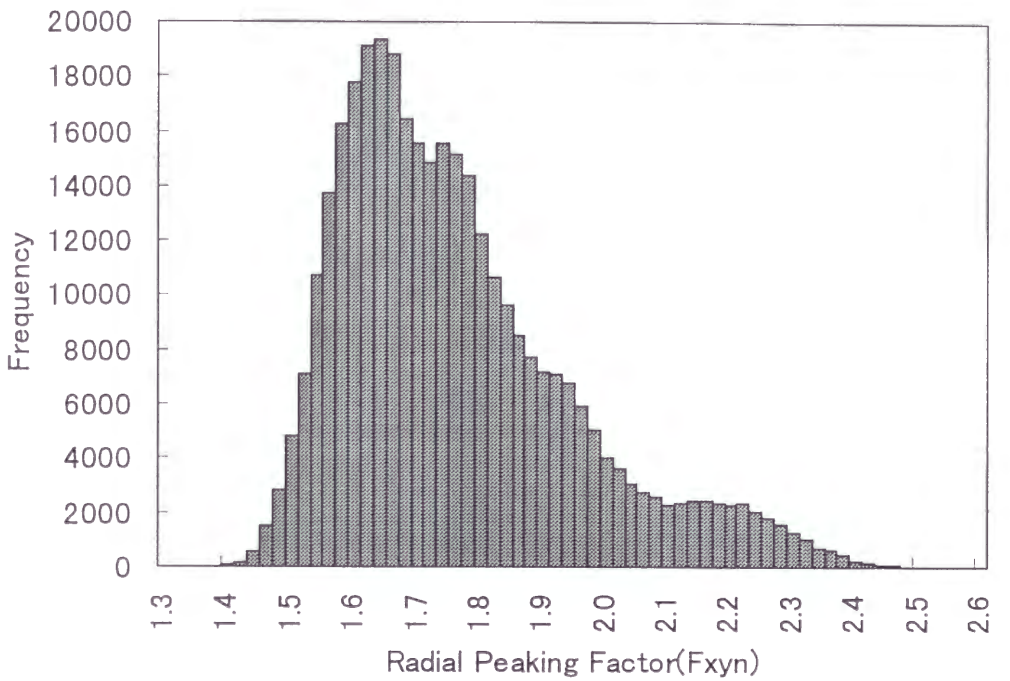

Fig. 3-3 Frequency distributions of radial peaking factor (Fxyn) in the database of single cycle optimization benchmark problem.

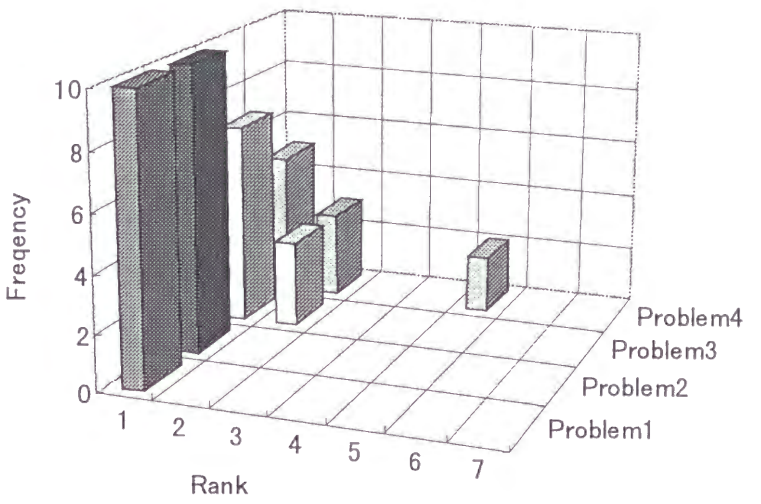

Fig. 3-4 Summary of calculated results for the single cycle optimization benchmark problem.

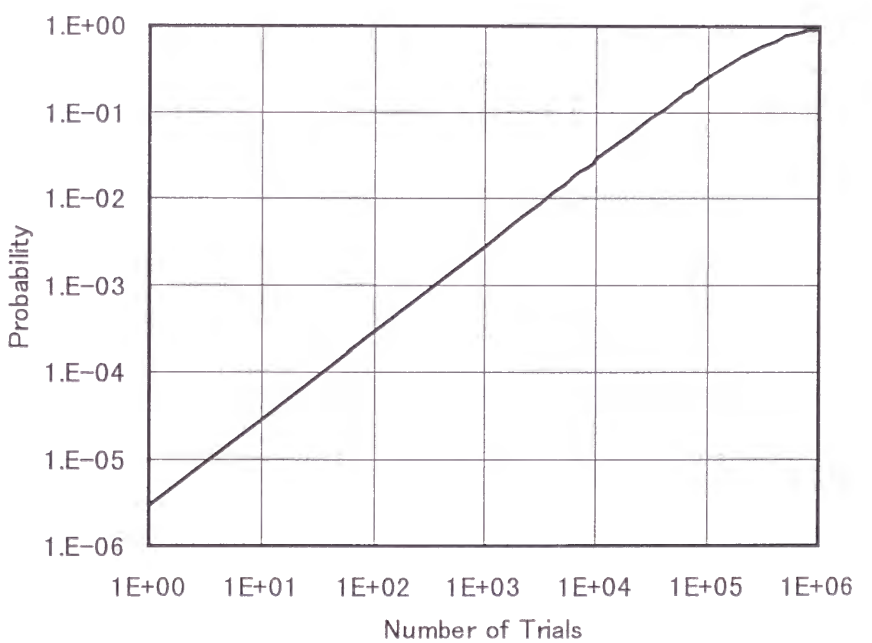

Fig. 3-5 Probability of reaching a true optimum solution through a random search strategy in the optimization benchmark problem for a single cycle.

CHAPTER 4

INSIGHT: AN INTEGRATED SCOPING ANALYSIS TOOL FOR IN-CORE FUEL MANAGEMENT OF PWR

4.1 Introduction

The fuel management scoping analysis[1], which determines fuel loading schematics during several successive cycles, becomes more and more important because it has a significant impact on the economics of the fuel cycle cost. Moreover, since high burnup fuels, reprocessed uranium fuels, gadolinia bearing fuels, and so on have been introduced into PWRs, the complexity of the in-core fuel management tasks is incleasing. Hence, the workloads of engineers, who are responsible for the in-core fuel management, are continuously increasing.

However, thanks to the recent advances in the powerful computer hardware, especially engineering workstations (EWSs) with the UNIX operating system and a graphical environment, sophisticated software workbenches which support the in-core fuel management have been developed[2],[3],[4]. These software workbenches are characterized by an interactive graphic user interface (GUI), an integrated database and advanced automation/optimization capabilities, and they are useful to greatly reduce the workload of the engineers.

A scoping analysis tool for the in-core fuel management of PWR, INSIGHT, has been developed with an aim of establishing this kind of workbench and to gain an "insight" into an economical fuel management strategy. Though the primary target of the previous works[2],[3],[4] was a workbench for the single cycle, that of INSIGHT is a workbench for the multicycle. Therefore, INSIGHT includes extended multicycle capabilities, which were not realized previously. INSIGHT also

incorporates an LP optimization capability that is essential for an accurate and automated multicycle analysis.

In Sec. 4.2, a software environment, which was utilized for developing INSIGHT, will be described. INSIGHT is a large-scale software, so the choice of software tools and the programming strategy is important as well as the implementations of the analysis capabilities. In Sec. 4.3, methodologies used in major calculation modules of INSIGHT will be described. In Sec. 4.4, two benchmark problems will be analyzed by INSIGHT to confirm capabilities for the single cycle and multicycle analyses. These benchmark problems contain various practical constraints, which are somewhat difficult to consider through the previous scoping analysis codes. In Sec 4.5, a summary of this study will be provided.

4.2 Software Environment for Developing INSIGHT

The fuel management scoping analysis is an extremely complex task because it should treat various kinds of data, such as fuel assembly designs, burnable poison designs, loading patterns, irradiation histories of fuel assemblies, reactor operating histories, safety parameter limitations, and so on. In order to reduce such complexity, the object-oriented programming (OOP) technique[5] was fully adopted in the development of INSIGHT. The C++ language was used to accomplish this aim.

Using OOP, complex data can be treated as the object, which binds data themselves and methods which process the data included in the object. Because the object encapsulates or hides the data within it, an external function of the software system cannot access these data directly. Therefore, any undesirable

interference among the objects can be almost eliminated. For example, if the functions are too tightly coupled, it is difficult to perform the maintenance or enhancements of the software. In general, this kind of interference rapidly increases according to the scale of code system, and impedes improvements in the code system.

Several analysis tasks in INSIGHT, for example the reactor core calculation, were implemented as objects. Consequently, the analysis capabilities of INSIGHT can be enhanced easily because these tasks were encapsulated from the other parts of INSIGHT.

Since INSIGHT was designed as an interactive software tool, it was developed on the UNIX workstations (HP735 series) equipped with an X-window system. GUI of INSIGHT was mainly constructed using the OSF/Motif toolkit.

4.3 INSIGHT Methodology

4.3.1 System Overview

The targets of INSIGHT are as follows:

- To reduce the workload of the fuel management scoping analysis for successive several cycles.
- To improve the accuracy of the fuel management scoping analysis.
- To reduce the fuel cycle cost by applying the LP optimization technique.
- To find out the fuel management scheme that is as economical as possible.

In order to realize these purposes, INSIGHT has several distinguished features:

- Menu driven, window based and interactive graphical user interface.
- Multi-objective LP optimization capability using the hybrid genetic algorithms. This task provides high quality LPs using flexible objective functions.
- Automated and accurate multicycle analysis utilizing the LP optimization capability.
- An integrated database to manage all kinds of data, which includes not only the results of scoping analysis but also the follow-up data of the actual core and calculated results. This database frees engineers from trivial but complex jobs such as the maintenance of the restart (or wrap up) files for the core calculation codes.
- Seamless interface among several tasks. For example, LPs generated by the optimization tasks are easily transferred to the interactive LP design tasks, and can be modified manually, and vise versa.

The basic structure of INSIGHT is shown in Fig. 4-1. In order to reduce complex operations, INSIGHT is designed to operate only through the task manager, which controls the analysis modules. Each analysis module, which performs various calculations, is kicked from the task manager according to the user's operation. When the analysis has completed, the results are transferred from the analysis module to the task manager. The task manager edits the analysis results and provides a summary to the user.

INSIGHT has three main analysis modules; an LP optimization module GALLOP, an interactive LP design module PATMAKER and a multicycle analysis module MCA. In these analysis modules, GALLOP and MCA make the key distinguished features of INSIGHT described above. In the following part, the

explanations of these analysis modules will be described. The role of the database will be also briefly explained.

4.3.2 Loading Pattern Optimization Module (GALLOP)

In the scoping analysis of the in-core fuel management, the LP design task may be the most important, because the fuel cycle cost and the core safety parameters are determined mostly by LP. However, this task is also quite difficult and time consuming, and it requires state-of-art techniques of the engineers. Therefore, INSIGHT incorporates a flexible and robust LP optimization module, GALLOP[6], which is based on the hybrid genetic algorithm (GA). The genetic algorithm is one type of the optimization technique[7], whose basic concept is the evolution of life.

It is considered that GA is suitable for a global LP search because of its robustness for the multi-modality[8]. However, a weak point of GA is that it cannot perform a local fine search around an optimum solution. In general, GA reaches a near optimum solution very quickly. After that, however, the optimization process stagnates and does not get closer to the optimum any more.

One of the concepts to produce a breakthrough at this point is the application of a hybrid search algorithm. At the primary optimization stage, GA is used for the global search. After GA finds a point near an optimum solution, a local search is performed successively. By using the hybrid search algorithm, the quality of the solution is much improved without any significant increase in computation time. In the present study, we adopted the local search method based on the assembly binary exchange (BE).

The BE method tries all possible binary exchanges from a base LP, and

estimates the performance of generated LPs using the core calculation code. Then the BE method performs the best binary exchange which improves the performance of the base LP most effectively. After that, the generated LP is used as the base LP in the next step. These procedures are repeated until any possible binary exchange provides no improvement in the performance of the base LP. Note that the performance of LP is measured by the objective functions used in the GALLOP module.

There are many engineering requirements in the scoping analysis. To accommodate these requirements, GALLOP module can treat many objectives; the cycle length, the maximum burnup, the discharge burnup, the moderator temperature coefficient, the radial peaking factor, the cross radial power tilt, the target burnup band, and so on.

For the core calculation, a two-dimensional coarse mesh (2x2/assembly) diffusion calculation, which takes into account the feedback caused by the thermal-hydraulics behavior and includes the boron concentration search, is executed using the SHARP code. SHARP is the core calculation code of Nuclear Fuel Industries, Ltd. and the improved coarse mesh method[9] or the analytic nodal method[10] is used to obtain the neutron flux distributions. The radial peaking factor is obtained by the pin power reconstruction method[11] or by a rough estimation using the intra-assembly power gradient and the local peaking factors.

To improve the optimization performance, the assembly radial power distribution is roughly estimated by the neural networks[12] to save a computation time. Based on the predicted results of power distribution by the neural networks, LPs are screened and only remaining LPs are to be calculated by SHARP.

The required parameters for the optimization calculation can be interactively set up through GUI. The fresh, irradiated and/or re-inserted fuels/burnable

poisons also can be specified through GUI. Therefore, the workload to prepare the input data for the optimization calculation is reduced to a minimum.

Since an optimization calculation requires a considerable computation time, a tracking window can monitor the progress of an optimization calculation. Because the GALLOP calculation is performed as an independent process from INSIGHT itself, one can perform other tasks using INSIGHT during the LP optimization calculations.

The calculated LPs can be stored in the LP library of INSIGHT, so these LPs can be used in the other tasks. For example, calculated LPs can be modified using an interactive LP design module that will be described in the next section.

4.3.3 Interactive Loading Pattern Design Module (PATMAKER)

The interactive LP design module, PATMAKER, offers the GUI environment for the engineers who design LP manually. An example display of PATMAKER is shown in Fig. 4-2. Because PATMAKER is designed as a menu driven software, the user can perform almost all operations in PATMAKER by clicking and pointing: the core to core or the core to pool fuel/BP shuffling, the LP symmetry check, the depletion calculation, the isothermal temperature coefficient calculation, and so on. By utilizing GUI, the engineers can easily review many more LPs than the traditional character user interface used in the mainframe computers.

In INSIGHT, PATMAKER is usually used to modify LPs that are generated by the GALLOP optimization module. However, since PATMAKER has a capability to generate an initial LP automatically, PATMAKER is also quite useful as a stand-alone LP design tool. In PATMAKER, an initial LP is generated by the k-infinity matching to the reference LP or the heuristic rule based algorithms. Because this

rule base is written in a kind of simple macro language, engineers can easily modify these rules to match their requirement for LP.

4.3.4 Multicycle Analysis Module (MCA)

The multicycle analysis is one of the essential tasks in the fuel management scoping analysis. However, this task is essentially complex and time consuming, since the LP design work for the single cycle is somewhat complex and it depends on the engineers' state-of-art techniques. Therefore, a simple reactor analysis model without an accurate LP treatment[1] was traditionally adopted in the multicycle analysis. Though this kind of a simple analysis provided valuable information about the fuel management strategy, the results are not very accurate, especially for the maximum burnup of fuel assembly and/or the discharge burnup, etc. In order to obtain accurate results, the multicycle analysis that takes into account the LP dependence is inevitable[13]-[16].

MCA, which is a multicycle analysis module of INSIGHT, automatically generates the cycle specific LPs and evaluates the core characteristics for several successive cycles. Actually, the GALLOP optimization module or the automatic initial LP generating module of PATMAKER makes the LPs and these core characteristics are evaluated by the core calculation code. Because MCA is also implemented with a simple one point (0 dimensional) reactor model[1], a rough and quick estimation of the core characteristics can be also performed.

The sequence of analysis by MCA is shown in Fig. 4-3. The required user input data for the multicycle analysis are reduced to a minimum, and most of the other data are prepared automatically using the integrated database of INSIGHT. The number of fresh fuels is automatically adjusted to satisfy the planned cycle length.

The inventory of the burnable poison is adjusted under the limitation of the moderator temperature coefficient. The discharge fuel assemblies are usually selected according to their residual reactivity, however the forced reloading or discharging fuel assemblies can be specified interactively.

The fuel cycle costs of calculated batch/cycle schematics (e.g. fuel reloading schemes) are estimated in MCA using the COST module and compared with each other. The fuel reloading schemes are ranked according to their costs and displayed with other information such as the cycle by cycle LPs, the safety parameters, the region averaged burnup and so on. Therefore, a suitable fuel reloading scheme can be specified not only from the economical aspects, but also from the other contexts of the in-core fuel management.

4.3.5 Integrated Database

In order to treat the various data required for the fuel management analysis, two different databases are implemented in INSIGHT. The first one is called the basic database, which is composed of the plant follow up data, the plant geometry data, the analysis condition data, the safety limit parameter data, the plant operation planning data, the fuel specification data, and so on. By using the basic database, most of the input data for the analysis module can be automatically prepared by INSIGHT.

The second one is the loading pattern database, which archives LPs generated in INSIGHT. Using this database, LP can easily transferred from task to task. For example, the following analysis can be performed without any complicated data management; starting from an LP calculated by the multicycle analysis module (MCA), the detailed LP optimization calculation is performed by GALLOP, after

that the optimized LP is slightly modified by the interactive loading pattern design module, PATMAKER.

The LP database includes not only LP itself, but also the relations between the ancestor and offspring LPs. Hence the inheritance relationships among LPs can be easily depicted as shown in Fig. 4-4.

4.4 Applications

4.4.1 Single Cycle Loading Pattern Optimization

To verify the capability of INSIGHT, a benchmark problem of the single cycle LP optimization was set up. For the optimization calculations, the GALLOP module was used. The target reactor was a Westinghouse (WH) type 3 loop PWR, which had 157 fuel assemblies in the core. The benchmark core consisted of 24 fresh fuel assemblies without Gadolinia ("Gd" will be used as an abbreviation hereafter), 36 fresh fuel assemblies with Gd, 60 once burned fuels and 37 twice burned fuels as shown in Table 4-1. The fuel rod layout inside the assembly was 17 by 17, including 24 guide thimbles and 1 instrumental thimble. The ^{235}U enrichment of the fresh fuel was 4.1 wt%. The operating cycle length was assumed to be 15.2 GWd/t, which corresponded to about 13.5 effective full power months.

In the scoping analysis, there may be various requirements for the LP design. In order to manage such requirements, great flexibility in the optimization calculation is necessary. In this benchmark calculation, the following 4 different situations were considered;

Case 1: minimize the radial peaking factor (Fxyn),

Case 2: maximize the cycle length,

Case 3: maximize the discharge burnup,

Case 4: maximize the cycle length while limiting the maximum burnup of specified fuel assemblies (serial No. of 15 and 17 in Table 4-1) below 30 GWd/t.

The other constraints applied to these problems were as follows:

- The maximum burnup of the fuel assemblies should be below 48 GWd/t for all cases, except for the specified fuel assemblies in Case 4.
- The moderator temperature coefficient at the beginning of cycle under the hot zero power condition should be below -0.5 pcm/°C for all cases.
- Fxyn during the cycle burnup should be less than 1.480 for Cases 2, 3 and 4.

Case 1 is a simple optimization problem. However, the constraints of Cases 2 and 3 are almost the same as actual scoping analyses. The constraints of Case 4 are more complicated but realistic in consideration of the multicycle fuel management. Namely, if one has no consideration about the specified fuel assemblies (serial No. of 15 and 17 in Table 4-1) in the LP generation, these burnups may reach around 35 GWd/t at the end of cycle. Consequently, it becomes difficult to reload these fuel assemblies into the next cycle because of the maximum burnup limitation (48GWd/t). However, if the burnup of these fuel assemblies can be lowered below 30GWd/t, they have a possibility to be reloaded into the next cycle.

In the optimization calculation by the GALLOP module, about 3000 LPs were evaluated in each case. It took about 5-6 hours for each case using a HP735/99 workstation. The summary of calculated results are shown in Table 4-2. Figure 4-5 shows the final LP for each case calculated by the GALLOP module. From Table

4-2, the GALLOP optimization module generated adaptive LPs for the specific constraints of each case while satisfying the various safety limitations. In these calculations, all constraints were given by the input data and no modification was performed in the program. Consequently, the GALLOP module is quite useful for the scoping analysis of the fuel management because it can easily respond to the various engineering requirements for LPs.

4.4.2 Multicycle Loading Pattern Optimization

Recently, stack incidents of Rod Cluster Control (RCC), that RCC was not fully inserted into the WH fuel assembly of the 17 by 17 type with a relatively high burnup (around 40-45GWd/t or more), were reported at some USA reactors[17] [18]. Though the root cause is not completely clarified yet, one of the possible countermeasures is to exclude the high burnup fuel assemblies in the RCC positions. Because this countermeasure restricts freedom in the LP design space, it may reject the LPs with a good performance. In other words, by adopting this countermeasure, the discharge burnup may decrease and it may cause a negative impact on the fuel cycle cost.

A preliminary analysis was performed using the MCA multicycle analysis module in INSIGHT, to investigate the effect of this restriction on the discharge burnup. In order to perform this analysis, the cycle by cycle LP should be generated, hence it is impossible to carry out this analysis using traditional scoping analysis codes that utilize the one point reactor model.

The target reactor was again the WH type 3 loop PWR. Starting from the core whose fuel inventory was specified in the previous section, 10 successive cycles were calculated using MCA. LPs were generated using the GALLOP optimization

module, while the fuel inventory was adjusted using the MCA module. The discharged fuel assemblies were selected according to their burnup at the end of each cycle. The number of fresh fuel assemblies was determined to satisfy the required cycle length. Note that the ^{235}U enrichment of the fresh fuel was fixed to 4.1 wt% and the Gd bearing fuel was used as the burnable poison.

The constraints used in the LP optimization at each cycle were as follows;

1. Required cycle length was 15.2GWd/t.
2. Maximum Fxyn during the cycle burnup should be less than 1.435.
3. Maximum fuel assembly burnup at the end of cycle should be less than 48GWd/t.
4. Maximize the discharge burnup during optimization.
5. Maximum burnup of the fuel assemblies at the RCC positions should be less than 40GWd/t throughout the cycle burnup.

The constraints from 1 to 4 are ordinary ones, however, the last constraint 5, introduced to realize the countermeasure described above, is not ordinary. The last constraint was taken into account as a penalty function in the GALLOP optimization module. In order to investigate the last constraint's effect, a control case not including the last constraint was also performed.

About 2000 LPs were evaluated by the GALLOP module for each cycle. Therefore, about 20000 LPs were evaluated during successive 10 cycles and it took about 30 hours using the HP735/99 workstation for each case.

The summary of calculated results is shown in Table 4-3. If the constraint of the assembly burnup in the RCC position is considered, the average discharge burnup becomes lower and the number of required fresh fuel assemblies increases.

Since the difference in the fuel cycle cost between these two cases can reach the millions of dollars, it is considered to be sizable. The main cause of this result seems to originate in a reduction in the design space of LPs; this reduction makes more economical LPs unfeasible.

An example of the calculated LP is shown in Fig.4-6. The maximum burnup in the RCC positions at the end of cycle is 34.8GWd/t; the constraint of maximum burnup in the RCC position is satisfied. Because the number of calculated LPs in one cycle is not very many, this result is considered to be a proof that the GALLOP optimization module has a practical LP search capability.

4.5 Conclusions

An integrated scoping analysis tool for the in-core fuel management, INSIGHT, has been developed for pressurized water reactors. INSIGHT is a sophisticated workbench including following modules or functions;

- multi-objective LP optimization module, GALLOP, which adopts the hybrid genetic algorithms,
- interactive LP design module, PATMAKER,
- automated multicycle analysis module, MCA,
- integrated database,
- menu-driven, window-based, interactive GUI.

By utilizing these modules and functions, INSIGHT enables to reduce the workload of engineers, improve the accuracy of scoping analysis and reduce the fuel cycle cost.

The capability of two important INSIGHT modules, namely, the GALLOP LP optimization module and the MCA multicycle analysis module, was tested through the benchmark problems.

The capability of the GALLOP module was demonstrated through the LP optimization problem for a single cycle, which included various constraints. The LPs generated by GALLOP satisfied the safety limitations while maximizing objective values such as the cycle length or the discharge burnup. The results confirmed the practical and robust LP optimization capability of the GALLOP module.

MCA was applied to the LP optimization problem for the multicycle, which included uncommon constraints regarding a burnup limitation at the RCC position. Ten successive cycles were successfully calculated using MCA under the several constraints. The results showed the effectiveness of MCA for the multicycle analysis. The calculation results also indicated that the constraint of burnup limitation at the RCC position made the discharge burnup lower because of the reduction in the feasible design space of LP.

Through these benchmark problems, the important capabilities of INSIGHT for the in-core fuel management were confirmed.

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Table 4-1 Fuel assemblies used in the LP optimization problem for a single cycle.

Serial No.	Burnable Poisons	Burnups (GWd/t)	Number of Fuel Assemblies
1	Gd*)	34.7	1
2	Gd	34.7	4
3	Gd	32.7	4
4	Gd	16.8	4
5		23.0	4
6	Gd	19.5	4
7	Gd	32.2	4
8	Gd	16.8	4
9		28.9	4
10		12.6	4
11		12.6	4
12	Gd	0.0	4
13		23.8	8

Serial No.	Burnable Poisons	Burnups (GWd/t)	Number of Fuel Assemblies
14	Gd	18.9	8
15	Gd	19.0	8
16		27.9	8
17	Gd	18.4	8
18		11.3	8
19		10.2	8
20	Gd	0.0	8
21	Gd	0.0	8
22	Gd	0.0	8
23	Gd	0.0	8
24		0.0	8
25		0.0	8
26		0.0	8

*) Gd shows Gadolinia bearing fuel.

Table 4-2 The calculation results of the LP optimization problem for a single cycle. These results were calculated by the GALLOP LP optimization module.

Case	Cycle Length (GWd/t)	Maximum Burnup (GWd/t)	Fxyn	Moderator Temperature Coefficient (pcm/°C)	Discharge Burnup (GWd/t)	#15,17 Fuel Burnup*) (GWd/t)	Remarks
1	15.304	47.118	1.3565	-3.9	39.661	36.779	Minimize Fxyn
2	16.349	46.898	1.4771	-0.6	38.252	37.122	Maximize Cycle Length
3	15.282	47.305	1.4777	-0.9	40.495	38.325	Maximize Discharge Burnup
4	16.198	47.081	1.4717	-0.7	38.196	28.668	#15,17Burnup<30GWd/t

*) The burnup of fuel assemblies at the end of cycle whose serial No. are15 and 17 in the Table 1.

Table 4-3 The calculation results of the LP optimization problem for the multicycle. These results were calculated by MCA and the GALLOP LP optimization module for successive 10 cycles.

Restriction	Sum of Fresh Fuels for 10 cycles	Average Discharge Burnup (GWd/t)
a	576	41.380
b	572	41.555

a: Considers the burnup limitation at the RCC positions.
b: Does not consider the burnup limitation at the RCC positions.

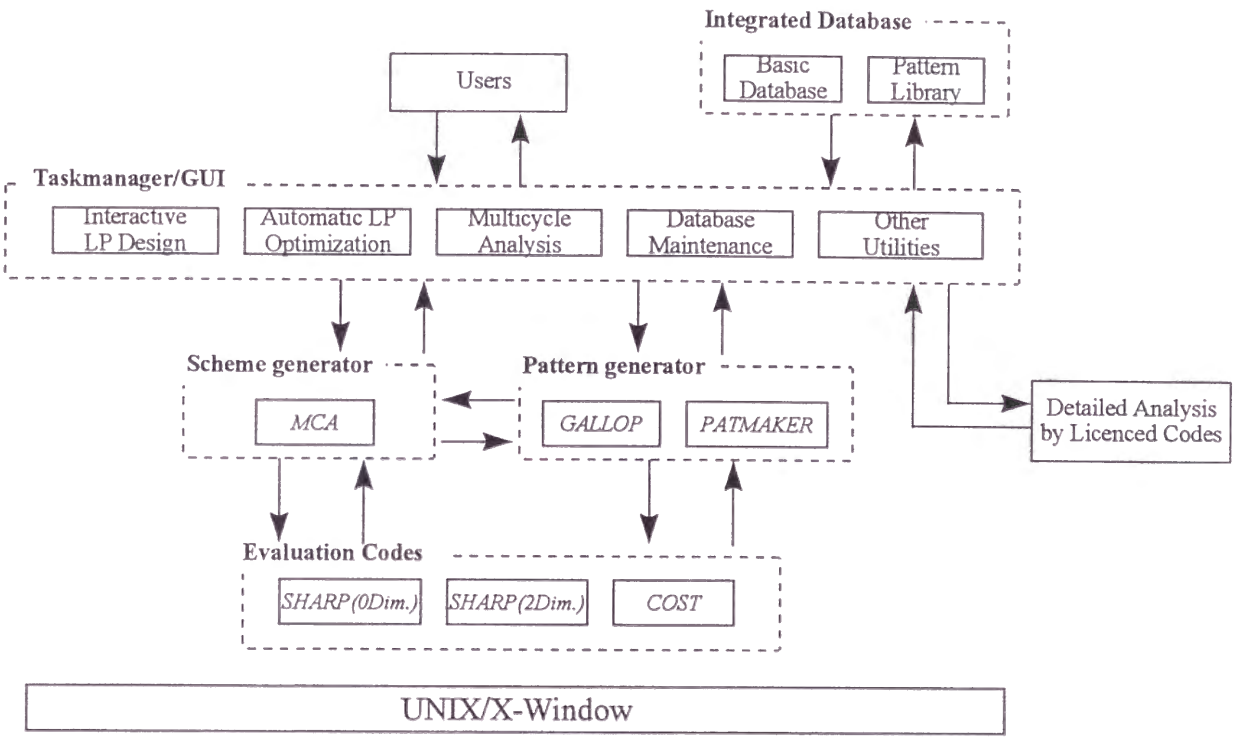

Fig. 4-1 An overview of INSIGHT in-core fuel management system.

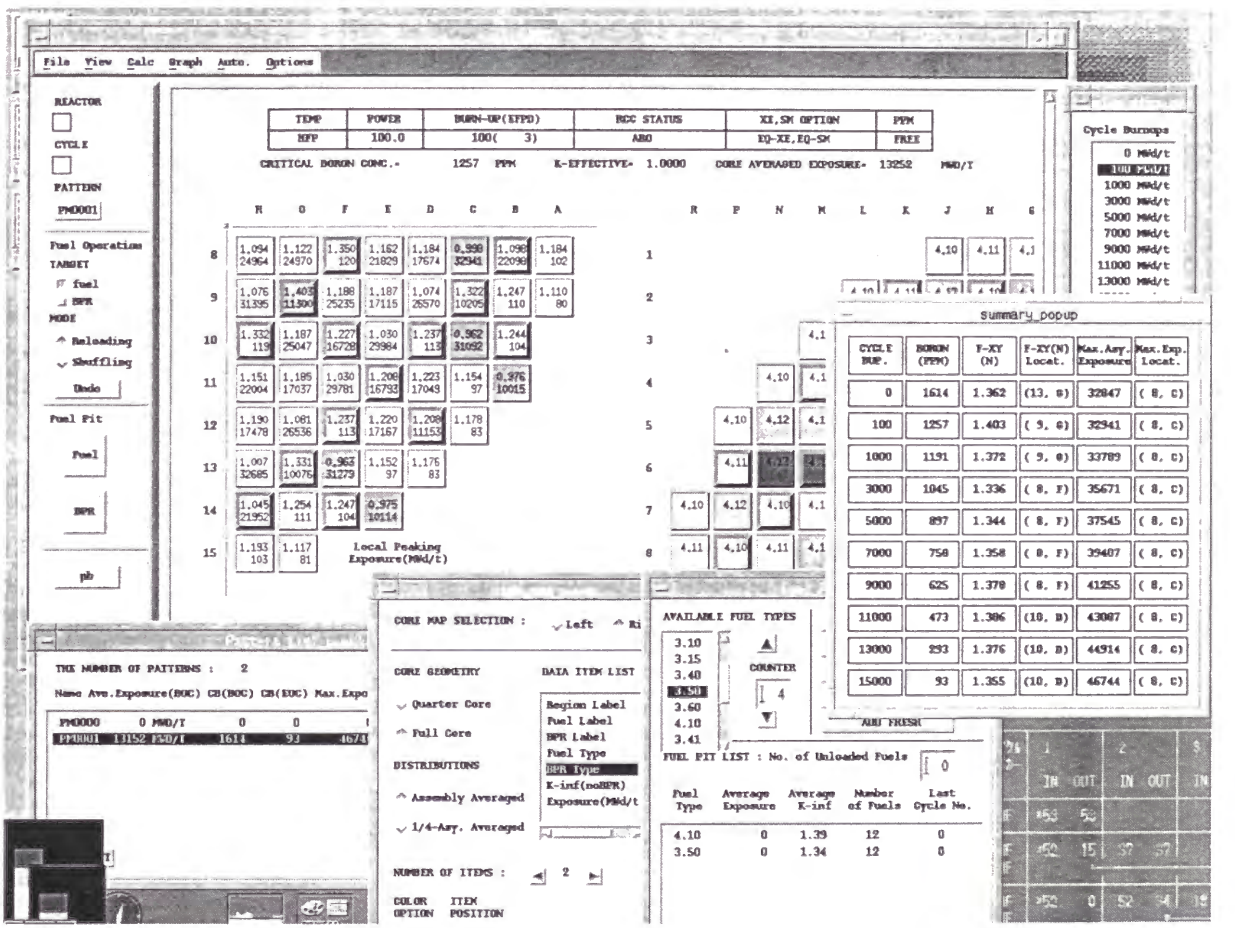

Fig. 4-2 An example display of an interactive LP design module, PATMAKER.

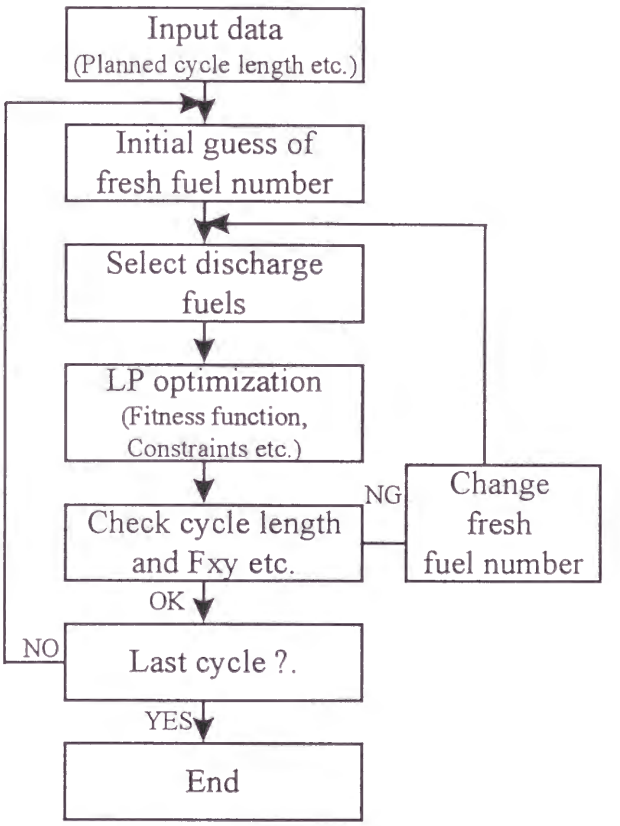

Fig. 4-3 Calculation Scheme of the multicycle analysis by the MCA module.

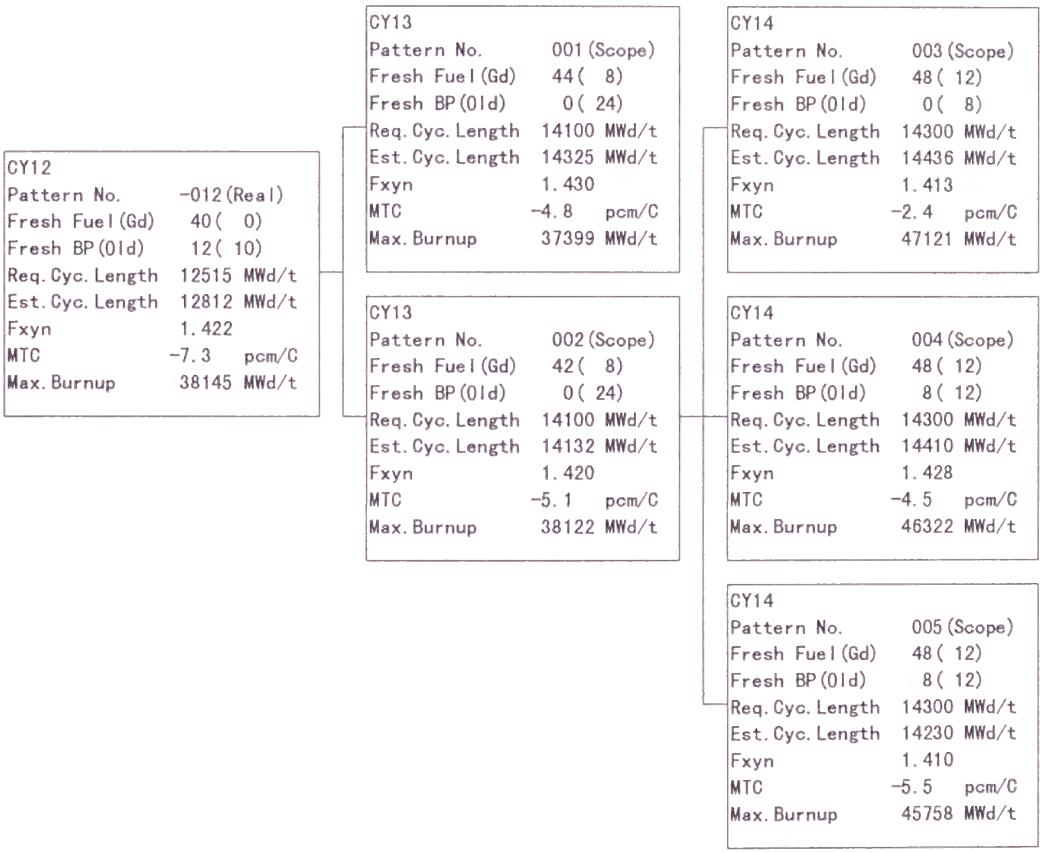

Fig. 4-4 An example display for the inheritance relationships of LPs in the successive cycles.

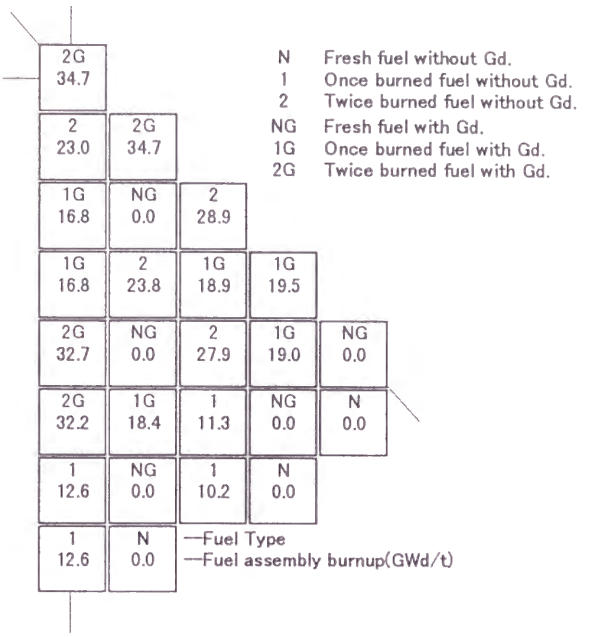

Fig. 4-5(a) The calculated LP of Case 1 (Minimize Fxyn) in the LP optimization problem for a single cycle by the GALLOP optimization module

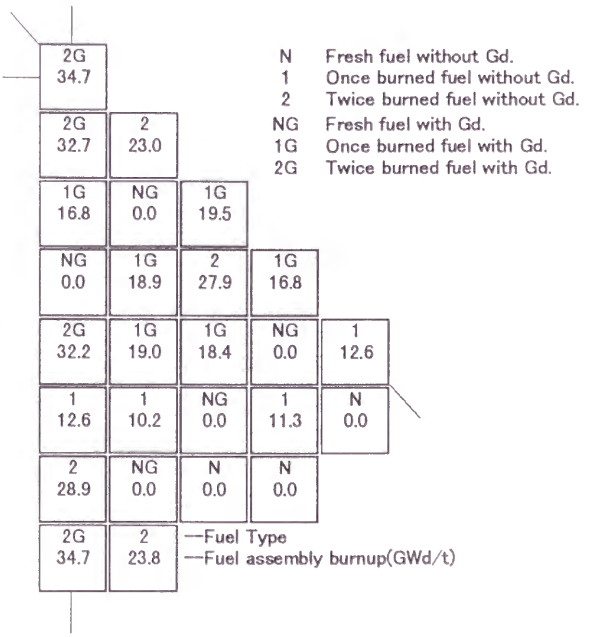

Fig. 4-5(b) The calculated LP of Case 2 (Maximize cycle length) in the LP optimization problem for a single cycle by the GALLOP optimization module.

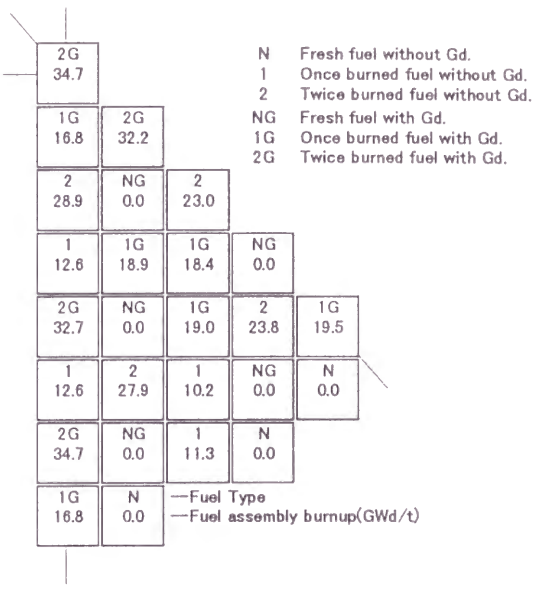

Fig. 4-5(c) The calculated LP of Case 3 (Maximize discharge burnup) in the LP optimization problem for a single cycle by the GALLOP optimization module.

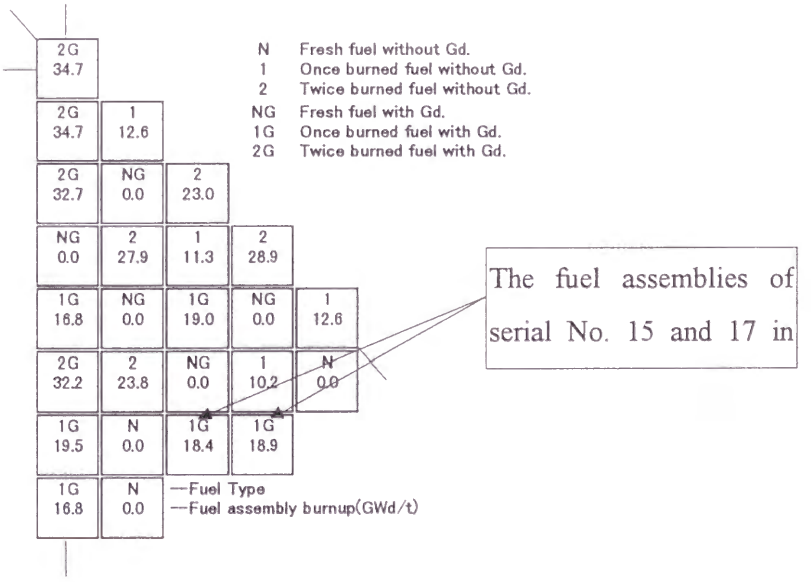

Fig.4-5(d) The calculated LP of Case 4 (Maximize discharge burnup while limiting maximum burnup of serial No. 15, 17 assemblies shown in Table 1 below 30GWd/t) in the LP optimization problem for a single cycle by the GALLOP optimization module.

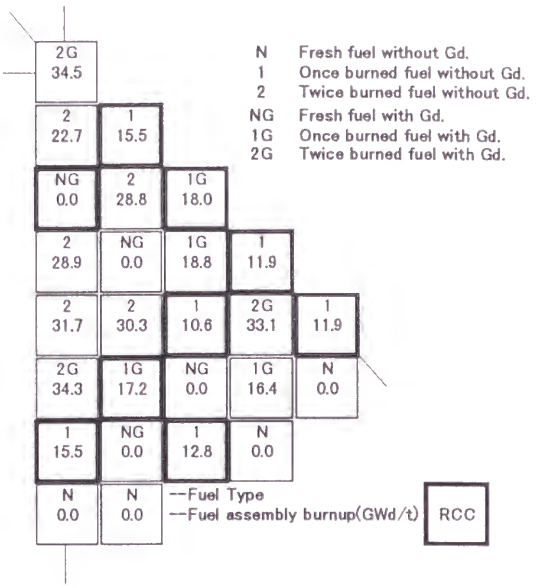

Fig. 4-6(a) An example of the LP in the LP optimization problem for multicycle. This figure indicates the burnup distribution at the beginning of cycle.

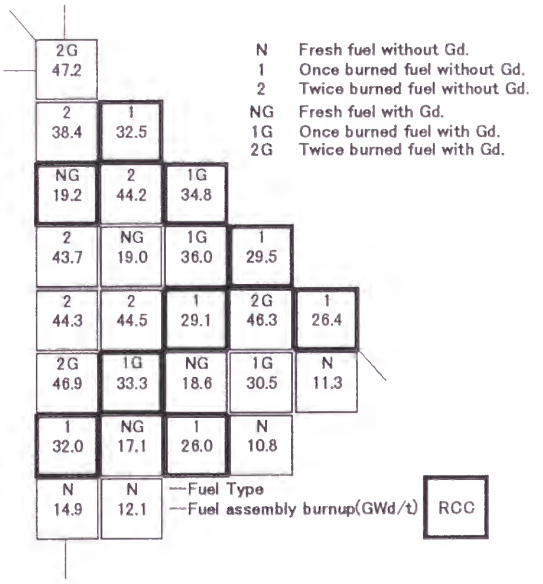

Fig. 4-6(b) An example of the LP in the LP optimization problem for multicycle. This figure indicates the burnup distribution at the end of cycle.

CHAPTER 5

COMPARISON BETWEEN EQUILIBRIUM CYCLE AND SUCCESSIVE MULTICYCLE OPTIMIZATION METHODS FOR IN-CORE FUEL MANAGEMENT OF PRESSURIZED WATER REACTORS

5.1 Introduction

According to the current fuel management strategy for pressurized water reactors (PWRs), fuel assemblies are loaded in-core during several cycles. Therefore, the fuel loading pattern in each cycle essentially depends on those of the previous cycles. Furthermore, the reactor operating period is not the same in each cycle, e.g. an earlier shutdown due to a certain trouble or change in the plant operating plan itself. Consequently, the loading pattern is different in every cycle. Since an equilibrium cycle can be considered to be a typical core, an analysis of the equilibrium cycle is useful for evaluating economics and/or safety of the newly designed fuel assemblies.

Creation of an equilibrium loading pattern is considered to be more difficult than that of a single cycle in two aspects:

(1) For an equilibrium cycle, a loading pattern is determined by *reloading* pattern that indicates the fuel shuffling method between two consecutive cycles as will be discussed in Sec. 5.2.1. Shuffles of the reloading pattern should be performed with an attention since the reloading pattern does not represent the fuel assemblies themselves. For example, shuffles of the reloading pattern do not always guarantee

the proper equilibrium core that consists of the proper fuel inventories.

(2) Much computation time is needed to obtain the equilibrium core characteristics because the iterative burnup calculation is inevitable.

Therefore, a series of parametric surveys using equilibrium cycles is considered to be time consuming though such evaluation work can be utilized for various purposes.

For example, in order to evaluate the cost merit from the relaxation of the peaking factor restriction, many equilibrium cycles should be calculated under various operating conditions. Furthermore, the created equilibrium cycles should be optimized to the same grade, otherwise the equilibrium cycles cannot be quantitatively compared with each other. Such work is quite tedious and exhausting for engineers.

Since the equilibrium cycle optimization is much more complicated than the single cycle optimization, there are very little associated researches. R. van Geemert et al.[1] have recently studied the optimization for the equilibrium cycle, though their target was restricted to an ideal PWR core much smaller than a full-scale commercial PWR. Unfortunately, their optimization study did not cover various constraints that are essential in actual optimization calculations. For example, limitation on the maximum burnup and the moderator temperature coefficient were not considered throughout their study. Furthermore, because their research has been carried out concerning the optimization method, there was no comparison with the conventional method like a successive multicycle optimization. Such comparison is quite fruitful for discussing the fuel management strategy.

Considering the above, a loading pattern optimization code for an equilibrium cycle, OPAL, has been newly developed via the present study. The OPAL code is

based on the simulated annealing method[2] and it can treat a full-scale PWR core for practical use.

In order to verify the capability of the OPAL code, a comparison with a successive multicycle optimization, which performs optimization through successive cycles, was executed. In order to clarify the concepts of the equilibrium cycle and successive multicycle calculations, these concepts are illustrated in Fig. 5-1 for reference. Since successive multicycle optimization has been applied to the actual in-core fuel management, this comparison is valuable to clarify the capability of the equilibrium cycle optimization.

The comparison between the equilibrium cycle and the successive multicycle optimization will also provide another interesting aspect. The equilibrium cycle has a unique feature that the discharge burnup is proportional to the cycle length[3]. On the other hand, the discharge burnup is not proportional to the cycle length in a single cycle optimization; actually, the discharge burnup sometimes shows a reverse trend against the cycle length. In general, the discharge burnup is considered to be an optimization index for the long-term fuel management, whereas the cycle length is that for the short-term fuel management. It means that there is a kind of tradeoff between the discharge burnup and the cycle length in the successive multicycle optimization.

In Sec. 5.2, the optimization methods used in the present study will be briefly described. In Sec. 5.3, the numerical results obtained by the equilibrium cycle and the successive multicycle optimizations will be described and compared with each other. In Sec. 5.4, conclusions from this study will be summarized.

5.2 Optimization Methods

5.2.1 Equilibrium Cycle Optimization Method

An equilibrium cycle is defined as a steady state loading pattern with the fixed number of fresh fuel, feed enrichment, inventory of the burnable poison and fuel reloading between two consecutive cycles. So the core characteristics such as the discharge burnup and the cycle length do not change cycle by cycle; these characteristics are identical in every cycle. The equilibrium cycle can be attained through the repetition of cycle burnup calculations assuming an identical fuel reloading throughout consecutive cycles.

Most of the loading pattern optimization methods are based on the shuffles of fuel assemblies; assemblies are directly swapped with each other to obtain a better solution. However, in an equilibrium cycle, the fuel assemblies cannot be swapped directly because the equilibrium cycle loading pattern is represented not by the fuel *loading* pattern but by the fuel *reloading* pattern as shown in Fig. 5-2. If the shuffles based on the reloading pattern are performed without an attention, the fuel inventory of the equilibrium cycle cannot be guaranteed. For example, the reloading pattern shown in Fig. 5-3 is generated from Fig.5-2 (b) by swapping the locations "F,12" and "E,13". According to the reloading pattern, the fuel assembly at the position "E,13" comes from "E,13". It means that the fuel assembly in this position is never discharged from the core.

In this study, the "fuel ID" that is based on the irradiated history of a fuel assembly and the "fuel ID pattern" that arranges the fuel ID in a core shape, are utilized in the optimization procedure to solve the difficulty described above.

Table 5-1 shows an example of fuel assemblies and their fuel IDs used in an equilibrium cycle of the 3 loop Westinghouse-type PWR. Figure 5-4 shows an

example of the fuel ID pattern and the "decoded" fuel reloading pattern that consists of the fuel assemblies shown in Table 5-1. The fuel reloading pattern shown in Fig. 5-4(b) is decoded by tracking the cycle by cycle movement of the fuel assembly on the fuel ID pattern shown in Fig. 5-4(a). Note that since Fig. 5-4 is shown as an octant core, the fuel IDs shown in Table 5-1 appear once in Fig. 5-4 excluding on the symmetric line. For example, "G,9" and "D,12" have four symmetric positions in the full core, otherwise "E,14" has eight symmetric positions.

The loading pattern optimization is performed on the basis of the fuel ID pattern shown in Fig. 5-4. In other words, a candidate of the optimized fuel ID pattern is generated using an optimization method, and the candidate is decoded into a fuel reloading pattern. After that, iterative burnup calculations to obtain the equilibrium cycle are performed using the identical fuel reloading throughout consecutive cycles. From preliminary calculations, approximately five iterations were required to attain an equilibrium state when the two dimensional core calculation was utilized to evaluate the core characteristics. During the iterative calculations, precise evaluations such as a pin power reconstruction are not necessary, because only an assembly burnup distribution at the end of cycle is essential to evaluate the core characteristics of the following cycle. Therefore, a calculation time to attain equilibrium cycles is considered to be less than one fifth of that needed in the core calculation for the single cycle.

Since the nature of the optimization problem for the equilibrium cycle is considered to be almost the same as that for the single cycle, a stochastic optimization method, which can overcome the multi-modality of the solution[4] [5], is required to obtain a high quality solution. Both simulated annealing and genetic algorithms are considered to be candidates of the stochastic optimization method

because they have been successfully applied to the loading pattern optimizations for the single cycle[6]-[13].

The simulated annealing method was adopted in this study because of its affinity with the fuel ID treatment described above. A permutation of the loading pattern, which is performed by successive fuel swaps, is directly performed on the fuel ID pattern and the reloading pattern of the candidate is generated through the decode procedures. The computational procedures of the equilibrium cycle optimization in this study are shown in Fig. 5-5.

A computer code, OPAL, was newly developed to perform the optimization of an equilibrium cycle based on the procedures described in Fig. 5-5. Since the OPAL code was developed as a practical tool for the optimization of an equilibrium cycle, it can take into account various core characteristics through the objective functions; the cycle length, the maximum burnup, the moderator temperature coefficient, the radial power tilt, the radial power peaking factor, the discharge burnup, the assembly relative power density at the specific core location, and so on. The OPAL code also utilizes many heuristic rules[9] [12] for maximizing the efficiency of the optimization calculations.

5.2.2 Successive Multicycle Optimization Method

The successive multicycle calculation, which performs a cycle by cycle optimization through successive cycles, is steadily gaining support since the calculated results are much more accurate than those of the traditional linear reactivity model[14]. The successive multicycle optimization requires much computation time since it performs repetitive loading pattern optimizations cycle by cycle. But the recent progress in computer hardware has made it feasible.

An optimization code for the loading pattern of a single cycle is necessary to perform the successive multicycle optimization. In this study, the GALLOP loading pattern optimization code[12] was used in the loading pattern optimization for a single cycle. The GALLOP code adopts the hybrid genetic algorithm, which combines a genetic algorithm for a global search method and the assembly binary exchange for a local search method[13]. The hybrid genetic algorithm has been successfully applied to the loading pattern optimizations of the single cycle, and it was demonstrated through benchmark calculations that the hybrid genetic algorithm is robust and effective for these problems[13]. Since the GALLOP code is a practical optimization code of the PWR loading pattern, it can take into account as many core characteristics as the OPAL code.

The MCA multicycle analysis code[15] was used to define the discharged fuel assemblies in each cycle. MCA has the capability to search the inventory of the fresh fuel assemblies and the burnable poisons under the condition of the required cycle length and under the limitation of the moderator temperature coefficient. The GALLOP code is automatically invoked by the MCA code in each cycle, and inventories of the fuel and burnable poison are given by MCA as input data.

The successive multicycle optimization is performed according to the procedures shown in Fig. 5-6. Note that the number of fresh fuel assemblies in each cycle was assumed to be fixed in the benchmark problem of this study; the fresh fuel and/or the burnable poison inventory was not adjusted.

5.3 Calculations

5.3.1 Definitions of Benchmark Problem

In order to make a comparison between the equilibrium and the successive

multicycle optimization methods, a benchmark problem has been setup. The target reactor was an Westinghouse-type 900 MWe PWR loaded with 17x17 fuel assemblies and the total number of the fuel assemblies in the core was 157. The number of the fresh fuel assemblies in each cycle was fixed at 56. Note that the ^{235}U enrichment of the fresh fuel was fixed at 4.1wt% and 32 Gadolinia bearing fuel assemblies were included in the fresh fuel assemblies. Note that the number of Gadolinia bearing fuel assemblies was also fixed.

The objective of this benchmark is to maximize the total energy production during ten successive cycles. Since the core characteristics of the equilibrium cycle are identical in each cycle, the total energy production during ten cycles can be easily obtained; ten times of that in the equilibrium cycle length. On the other hand, the cycle length obtained by the successive multicycle optimization is completely different in every cycle. Therefore, the total energy production during ten cycles is calculated by summing up that of each cycle length.

The fuel reloading was performed when the boron concentration of the core reached 10 ppm under the full power operating conditions. The other constraints used in this benchmark problem are as follows:

- the radial peaking factor should be lower than 1.480,
- the maximum burnup of the fuel assembly should be lower than 48GWd/t,
- the moderator temperature coefficient should be lower than -0.5 pcm/℃,
- the octant core symmetric should be satisfied.

These constraints make the benchmark problem more realistic.

5.3.2 Optimization Calculations

In the optimization calculations of equilibrium cycle, the simulated annealing method was utilized as described in Sec. 5.2.1. In the simulated annealing optimization, the initial annealing temperature and annealing factor are considered to be the most important parameters. In order to escape from local optima in the design space, the initial annealing temperature should be set high enough. However, when the initial temperature is set too high, the computation time will increase without a significant improvement in the quality of solution. In this study, the initial threshold probability shown in Fig. 5-5 was set to 0.8 by adjusting the initial annealing temperature[9]. The annealing factor, which is also sensitive to the solution quality and the computation time, was set at 0.9[13]. During the simulated annealing calculations, candidate loading patterns were generated through two or three chain shuffles of binary or ternary fuel ID swaps[5] from the base fuel ID pattern.

In the successive multicycle optimization, a hybrid genetic algorithm was used as described in Sec. 5.2.2. In the optimization calculation by genetic algorithm, 100 loading patterns were evaluated in one generation and continued during 30 generations; the evolution was performed during 30 generations[13]. The local search by exhaustive fuel binary swaps[13] was subsequently executed from the optimization result by the genetic algorithm. Note that these optimization procedures were successively executed in each cycle.

As described in Sec. 5.3.1, the objective function of the benchmark problem is the total energy production during ten successive cycles. In the successive multicycle optimization, however, the total energy production cannot be maximized directly because the optimization is executed cycle by cycle; total energy production

should be maximized indirectly through the optimization in each cycle. Though an objective function that maximizes the length of each cycle looks appropriate for this benchmark problem, the reactivity carryover should be taken into account in the multicycle optimization because of the coupling effect between consecutive cycles.

Since the energy production is tightly coupled with the average discharge burnup, maximization of the discharge burnup in each cycle is considered to be an alternative objective function. These two objective functions (maximizing cycle length and discharge burnup) have the identical effect in the equilibrium cycle, but they have a somewhat different context in the successive multicycle optimizations; the maximization of the cycle length does not always coincide with that of the discharge burnup.

Consequently, four different optimization calculations, which consist of one equilibrium optimization and three successive multicycle optimizations, were performed as follows.

Case A : The equilibrium cycle optimization to maximize the cycle length.

Case B : The successive multicycle optimization to maximize the cycle length in each cycle.

Case C : The successive multicycle optimization to maximize the discharge burnup in each cycle.

Case D : The successive multicycle optimization to maximize both the cycle length and the discharge burnup in each cycle.

In the equilibrium cycle optimization, the maximization of the cycle length is consistent with that of the discharge burnup. Hence the objective function of Case D

is considered to have a property similar to that of Case A.

Since simulated annealing and genetic algorithm are the stochastic optimization methods, the calculated results inevitably depend on the random seed. Therefore, three trial calculations were performed in each case assuming different initial random seeds.

The core characteristics were evaluated using SHARP, which is an in-house core calculation code. SHARP is a two dimensional, two group diffuison theory code with the capability to take into account feedback effects caused by the thermal-hydraulics and fission products, to execute a boron concentration search during the burnup calculation, and to perform a pin power reconstruction[16]. In the SHARP calculations, the fuel assemblies are divided into 2x2 nodes, and the improved coarse mesh method[17] or the advanced nodal method[18] can be utilized to reduce the spatial mesh effect.

5.3.3 Results and Discussions

The equilibrium cycle and the successive multicycle optimizations were carried out for the benchmark problem using the OPAL, GALLOP and MCA codes. The calculated results are summarized in Table 5-2. The calculated results of the successive multicycle optimizations are the average of the ten cycles whereas those of the equilibrium cycle optimization are the "single cycle" results. Note that the multicycle calculations were performed taking over the result of trial 3 in the Case A calculation.

Figure 5-7 shows the reloading pattern and burnup distributions of Case A (trial 3). Figure 5-8 shows the burnup distributions of Case B (trial 3), Case C (trial 2) and Case D (trial 1) corresponding to the first cycle of successive multicycle

optimizations. Note that these trials provide the best result in each case.

The calculated results satisfy the constraints defined in Sec. 5.3.1. For reference, the detailed result of Case C (trial 2) multicycle optimization is shown in Table 5-3.

The total energy production during ten cycles can be obtained from the cycle length shown in Table 5-2 by multiplying 10. The result of Case C, which is the successive multicycle optimization, attains the maximum total cycle length of 153.73 GWd/t by averaging three trials. The result of Case D, whose total cycle length is 153.57GWd/t, is quite close to that of Case C. The result of Case A, which is the equilibrium cycle optimization and whose total cycle length is 152.83GWd/t, follows Case D. The total cycle length of Case B, 152.52GWd/t, is the minimum among the four different cases. The average discharge burnup of these four optimization calculations provides almost the same trend as that of the total cycle length; the results of Case C attains the maximum and Case D, Case A and Case B follow Case C in this order.

The total cycle length of Case A is shorter than that of case D, though the definition of their objective functions is similar. The shorter cycle length of Case A is considered to be caused by the limitation of the reloading in the equilibrium cycle. In other words, since the reloading patterns which guarantee the proper equilibrium core are quite few, as described in Sec. 5.2.1, the feasible design space of the equilibrium cycle optimization is much more restricted than that of the successive multicycle optimization. Therefore, better loading patterns can be found in the successive multicycle optimization.

Another possible reason can be found in the optimization methods used in each calculation. The optimization performance of the simulated annealing method with

an annealing factor of 0.9 was slightly worse than that of the hybrid genetic algorithm in the previous study[13]. Therefore, the slower annealing schedule might be needed to obtain a better solution by the simulated annealing method, though the computation time would become much longer.

Case B attained the longest length in the first cycle, as shown in Fig. 5-8. On the contrary, the total cycle length of Case B provided the shortest value, as shown in Table 5-2. This inconsistency can be explained by the lowest discharge burnup of Case B. In order to increase the cycle length, the loading pattern of Case B settles in the low-leakage one. The low-leakage loading pattern improves the neutron economy because of less neutron leakage from the core. Furthermore, high reactivity fuel assemblies are placed in-board (i.e. a high neutron importance area) and such fuel arrangement increases the core reactivity. However, the discharge burnup of the twice burned fuel assemblies tends to decrease since they are placed in the core periphery. That is to say, the property of the low-leakage loading pattern is considered to have a positive effect on the length of single cycle but have a negative effect on the total length of multicycle under the constraints of this benchmark problem.

The above explanation is supported by the fact that the loading pattern of Case A did not settle in the aggressive low-leakage loading pattern. Since the objective function of Case A is defined by the equilibrium cycle length that is equivalent to the total length of multicycle, it is considered to be more suitable to attain the multicycle optimal. Therefore the aggressive low-leakage loading pattern is considered to be avoided because of its negative effect.

In this benchmark problem, ten cycles were calculated in the successive multicycle optimization. If the number of calculated cycles increases, the difference

in the cycle length between Case A and Case B will become more significant because the difference in the discharge burnup was larger than that in the cycle length. Assume that Case B attains a near equilibrium state by increasing calculated cycles while maintaining its discharge burnup at 42.635 GWd/t. In this case, the cycle length of Case B will reach 15.207 GWd/t. It can be calculated using the simple relationship among the discharge burnup, the number of fresh fuels, the sum of fuels in-core and the cycle length[14], i.e. $42.635 \times 56/157 \cong 15.207$. It means that the cycle length of Case B will become shorter as the number of calculated cycles increases.

This phenomenon can be explained by a "horizon effect". The horizon effect means the round off in the successive multicycle optimization; the number of calculated cycles should be limited in the successive multicycle optimization from the viewpoint of computation time. The horizon effect is caused by neglecting the reactivity carryover at the end of the multicycle optimization. In Case B, a negative reactivity carryover is neglected by the horizon effect, hence the cycle length of Case B (15.252 GWd/t) is greater than that of the near equilibrium state(15.207 GWd/t). Here the negative reactivity carryover is caused by a higher core average burnup in the low-leakage loading pattern of Case B. Note that the equilibrium cycle optimization is not impaired by the horizon effect and it is an advantage in the quantitative comparison of core neutronic performances. For example, the core performance loaded with newly designed fuels can be compared with less ambiguity using the equilibrium cycle optimization.

The benchmark calculations were performed using HP-C160 workstations that were equipped with the HP-UX10.2 operating system. The evaluation of the core characteristics took about 3~4 s/pattern using the pin power reconstruction

capability. In the equilibrium cycle case, it took about 12-14 s/pattern. About 4000 loading patterns were evaluated in one cycle for each successive multicycle optimization and 7000 loading patterns were evaluated in the equilibrium cycle optimization. Consequently, an optimization calculation during ten successive cycles took about 40 hours, and an optimization calculation of an equilibrium cycle took 25 hours. Hence the equilibrium optimization is advantageous from a calculation time viewpoint. Note that since the core calculation code was compiled on HP-UX9.05, it was not optimized for the execution on HP-UX10.2.

5.4 Conclusions

An equilibrium loading pattern optimization code for PWR, OPAL, was newly developed using the simulated annealing method. Since the equilibrium loading pattern is defined by the reloading pattern, a fuel ID pattern that enables to trace the fuel reloading history was introduced in the optimization process. During the simulated annealing optimizations, fuel shuffles were performed based on the fuel ID pattern and the reloading pattern was subsequently decoded from the fuel ID pattern. This procedure made the optimization calculations significantly more effective.

In order to verify the capability of the OPAL code, the analyses of the benchmark problem were carried out. The objective of this benchmark problem was to maximize the total energy production during ten cycles under the fixed feed enrichment of fuel and the fixed number of fresh fuel assemblies. In addition to the optimization calculations for the equilibrium cycle, those for successive multicycles were also performed using three different objective functions for the single cycle; maximizing (1) the cycle length, (2) the discharge burnup, and (3) both the cycle

length and the discharge burnup in each cycle. The multicycle optimization calculations were carried out using the GALLOP loading pattern optimization code and the MCA multicycle analysis code.

Among these four different calculations, the successive multicycle optimization, which maximizes the discharge burnup in each cycle, attained the greatest energy production during ten cycles. Maximization of both the cycle length and the discharge burnup provided almost the same result as maximizing the discharge burnup. The cycle length maximization in each cycle gave the worst result in this benchmark problem, since the discharge burnup was suppressed to a lower value.

The result of the equilibrium cycle optimization was slightly inferior to that of maximizing both the cycle length and the discharge burnup in each cycle. Since the definition of the objective function in these two calculations is similar, the difference in the results is considered to be caused by the restriction of the reloading in the equilibrium cycles. In other words, the limited solution space (i.e. candidates) of the equilibrium cycle leads to the worse objective value in some aspects. The different optimization methods used in the equilibrium cycle and successive multicycle calculations are considered to be another reason for the inferior result mentioned above.

However, the equilibrium cycle optimization has an advantage in the quantitative comparison of the core neutronic performances since the successive multicycle optimization includes the "horizon effect", i.e. the ambiguity due to the limitation on the number of calculated cycles. Since the performance of the equilibrium cycle optimization has been found to be almost compatible with that of the successive multicycle optimization, the equilibrium cycle optimization is considered to be quite useful in the evaluation of newly designed fuels, the cost-

margin tradeoff under various operating condition, and so on. The equilibrium cycle optimization is also advantageous from a viewpoint of computation time, compared with the successive multicycle optimization.

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Table 5-1 Example of fuel assemblies and fuel IDs used in an equilibrium cycle of the 3 loop Westinghouse type PWR. The total number of the fuel assemblies is 157 and the number of the fresh fuel assemblies is 56.

Serial No.	Number of Assemblies	Irradiated Cycle		
		1	2	3
1	8	1–1	1–2	1–3
2	8	2–1	2–2	2–3
3	8	3–1	3–2	3–3
4	8	4–1	4–2	4–3
5	8	5–1	5–2	5–3
6	8	6–1	6–2	6–3*)
7	8	7–1	7–2	7–3**)

*) Only four out of eight fuel assemblies are loaded in the third cycle.
**) Only one out of eight fuel assemblies is loaded in the third cycle.

Table 5-2 Summary of the calculated results of the benchmark problem.

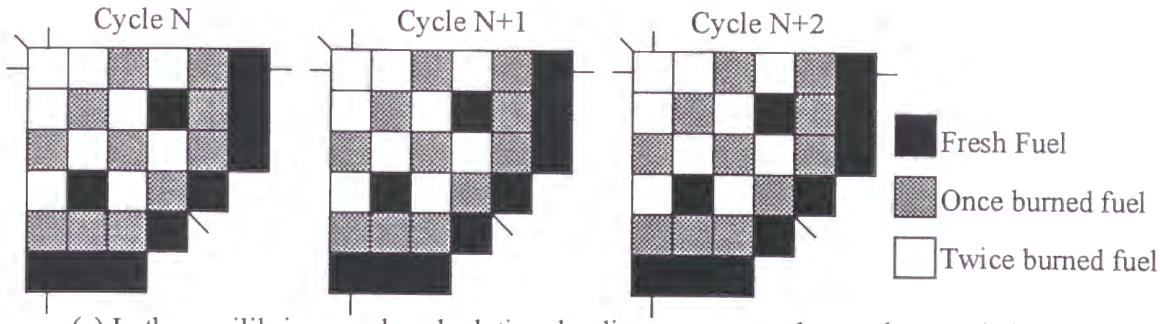
Case	Method	Trial	Cycle Length (GWd/t)	Maximum Burnup (GWd/t)	Fxyn	MTC (pcm/°C)	Discharge Burnup (GWd/t)	Remarks
A	Equilibrium	1	15.225	47.855	1.480	−3.5	42.684	Maximize cycle length.
		2	15.293	47.929	1.472	−3.2	42.875	
		3	15.332	47.971	1.477	−2.9	42.984	
		Average	15.283	47.918	1.476	−3.2	42.848	
B	Successive Multicycle	1	15.197	47.511	1.474	−4.4	42.577	Maximize cycle length in each cycle.
		2	15.267	47.586	1.479	−4.5	42.512	
		3	15.293	47.629	1.476	−3.8	42.815	
		Average	15.252	47.575	1.477	−4.2	42.635	
C	Successive Multicycle	1	15.349	47.956	1.475	−3.3	43.043	Maximize discharge burnup in each cycle.
		2	15.408	47.889	1.475	−2.8	43.165	
		3	15.364	47.755	1.477	−2.5	43.100	
		Average	15.373	47.867	1.476	−2.9	43.103	
D	Successive Multicycle	1	15.383	47.920	1.475	−2.6	43.149	Maximize both cycle length and discharge burnup in each cycle.
		2	15.371	47.851	1.476	−2.4	43.048	
		3	15.318	47.841	1.475	−3.2	43.049	
		Average	15.357	47.871	1.476	−2.7	43.082	

Note1: Fxyn and MTC indicate the radial peaking factor and the moderator temperature coefficient, respectively.
Note2: Values for Cases B through D are the average of the successive ten cycles calculations.
Note3: Trial means a series of the calculations using different random seeds.

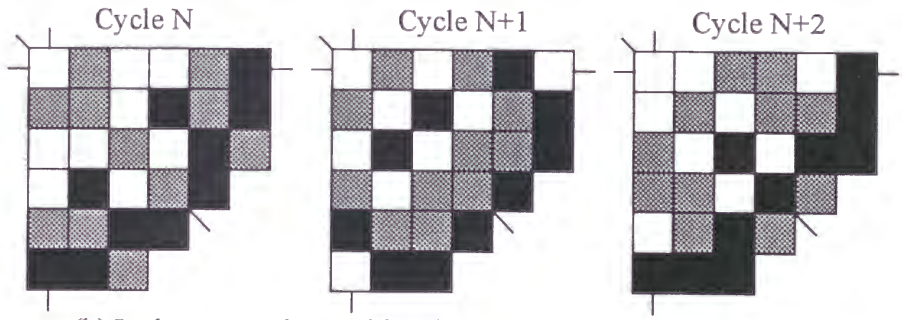
Table 5-3 Example of the successive multicycle calculation results; trial 2 of Case C.

Cycle	Cycle Length (GWd/t)	Maximum Burnup (GWd/t)	Fxyn	MTC (pcm/℃)	Discharge Burnup (GWd/t)
1	15.466	47.799	1.480	−1.9	43.629
2	15.618	47.851	1.473	−2.3	42.791
3	14.989	47.995	1.472	−4.7	42.993
4	15.530	47.571	1.478	−2.3	43.556
5	15.522	48.000	1.479	−2.4	42.959
6	15.537	47.946	1.472	−1.7	43.674
7	15.302	47.924	1.480	−3.3	42.581
8	14.951	47.859	1.479	−4.2	43.276
9	15.424	47.999	1.460	−3.6	43.029
10	15.736	47.947	1.478	−1.2	43.167
Average	15.408	47.889	1.475	−2.8	43.165

Note: Fxyn and MTC indicate the radial peaking factor and the moderator temperature coefficient, respectively.

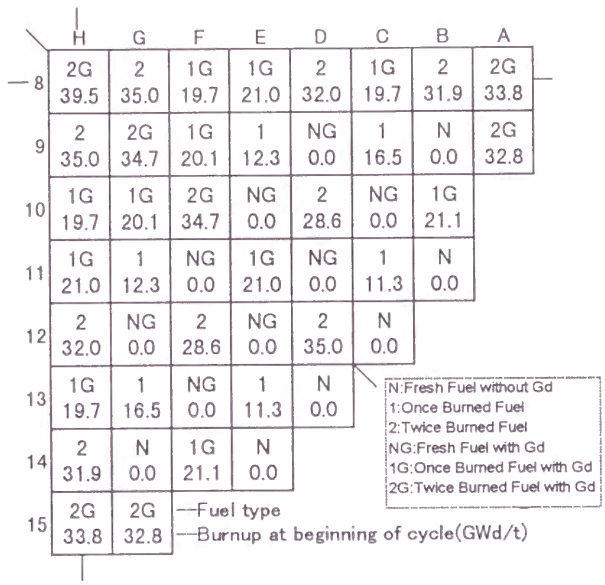


(a) In the equilibrium cycle calculation, loading patterns and core characteristics are identical in every cycle.

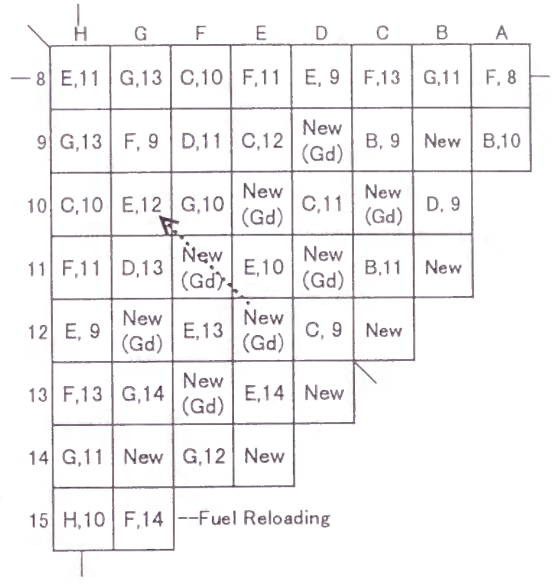


(b) In the successive multicycle calculation, loading patterns and core characteristics are different in every cycle. Therefore, generation of a loading pattern and evaluation of core characteristics are successively performed in each single cycle.

Fig. 5-1 Concept of the equilibrium cycle and the successive multicycle calculations in small ideal cores



(a) Example of fuel *loading* pattern. The *loading* pattern directly represents arrangement of the fuel assemblies. Note that Gd represents the Gadolinia bearing fuel.



(b) Example of fuel *reloading* pattern. The *reloading* pattern indicates the way of fuel shuffling from the previous cycle. For example, the fuel assembly located in "G,10" has been reloaded from the location "E,12", as indicated by the arrow.

Fig. 5-2 Comparisons of a fuel loading pattern and a fuel reloading pattern.

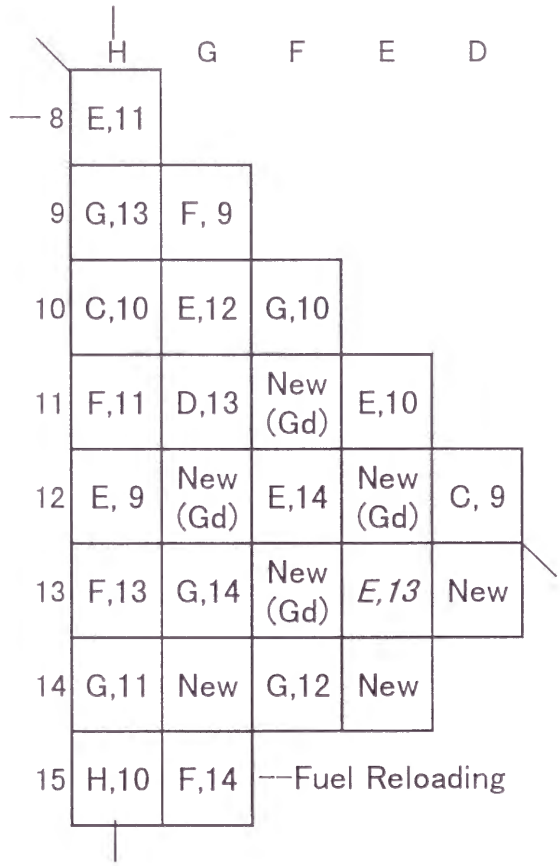
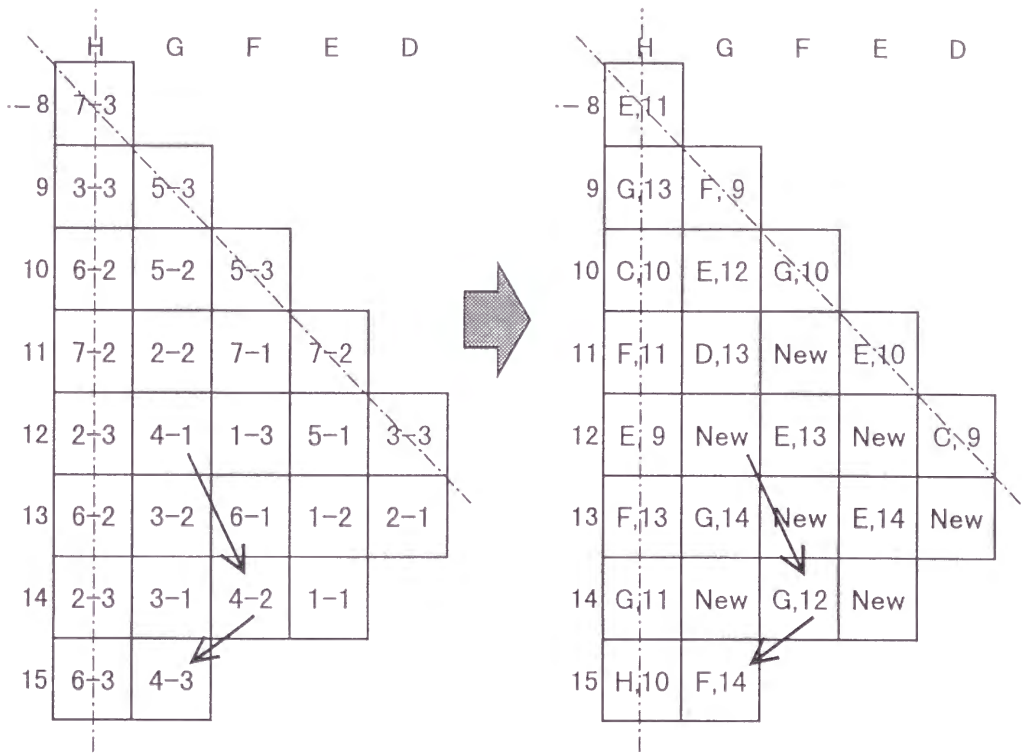


Fig. 5-3 Example of a wrong fuel reloading pattern.



(a) The fuel ID pattern consisted of the fuels shown in Table 1. The arrows corresponding to an example of the fuel reloading history. The fuel of serial No. 4 shown in Table 1 has been loaded at "G,12" as fresh fuel. This fuel has been reloaded successively to "F,14" and "G,15" in the consecutive two cycles.

(b) The fuel reloading pattern decoded from the fuel ID pattern. The fuel reloading can be identified through the trajectory of the fuel assembly. For example, the fuel loaded at "G,15" has been reloaded from "F,14".

Fig. 5-4 Example of the fuel ID loading pattern and the decoded fuel reloading pattern.

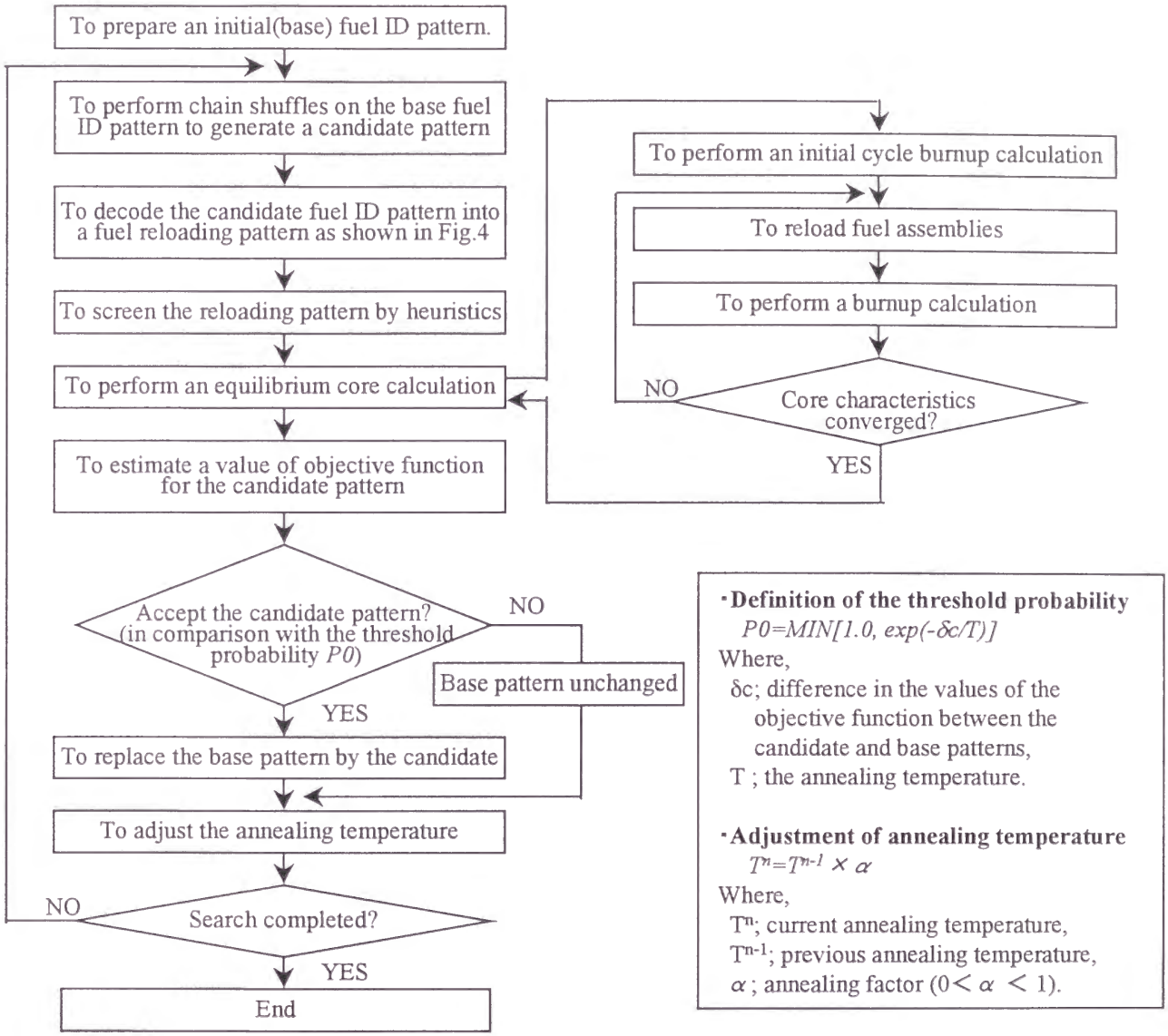


Fig. 5-5 Flowchart of the loading pattern optimization calculation for the equilibrium cycle using the OPAL code.

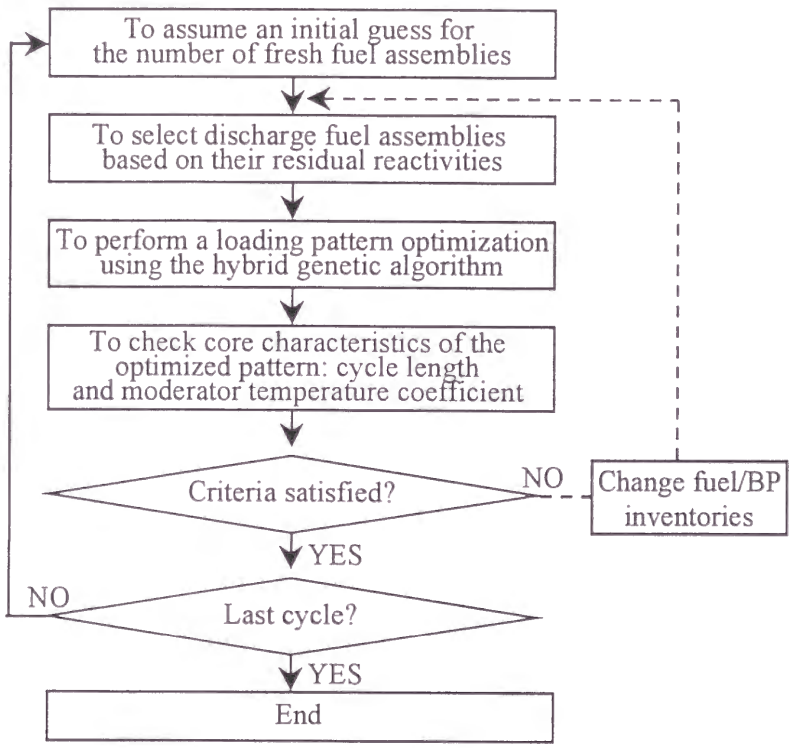


Fig. 5-6 Flow chart of calculation for the loading pattern optimization of the successive multicycle using the GALLOP and MCA codes.

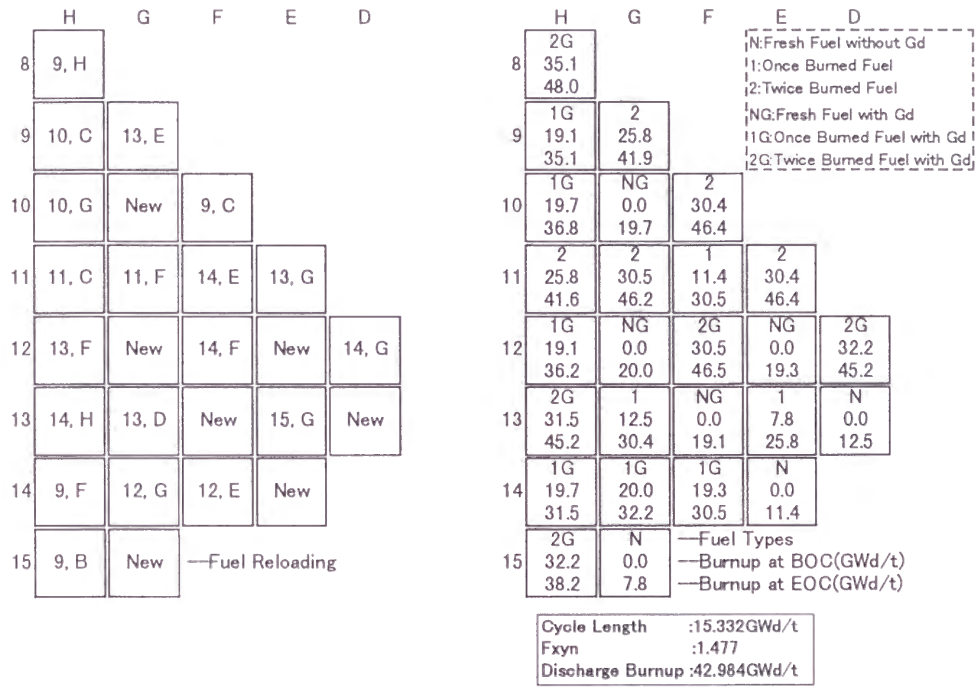


Fig. 5-7 Reloading pattern and burnup distributions of the trial 3 in Case A.

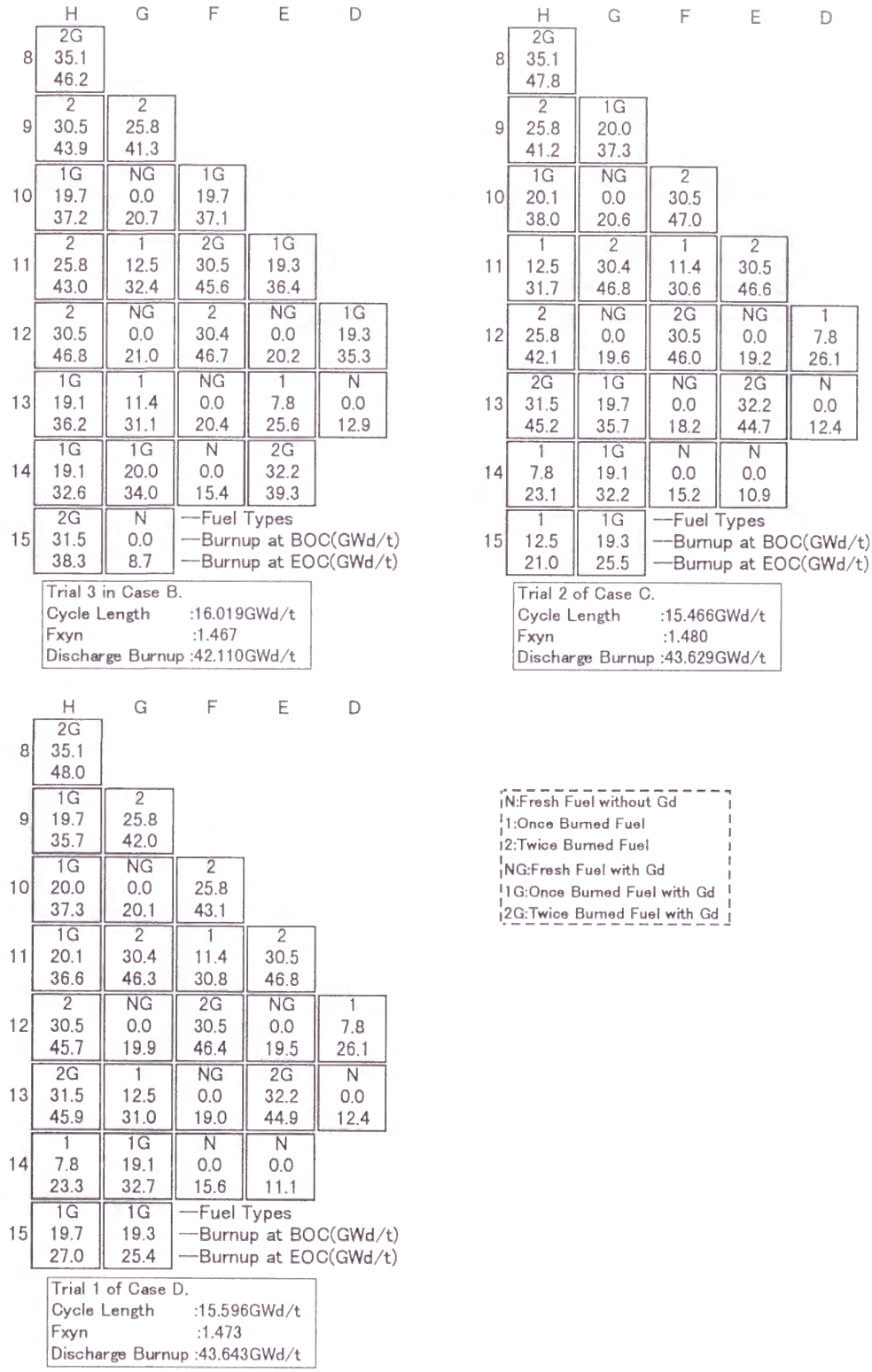


Fig. 5-8 Burnup distributions of the trial 3 in Case B, the trial 2 in Case C and the trial 1 in Case D. The results for the first cycle in the multicycle calculations are shown.

6. CONCLUSIONS AND A FUTURE VIEW

The present thesis described results of a study on the loading pattern optimization problem and its application to the practical in-core fuel management of pressurized water reactors (PWRs), which shares around a half of the Japanese commercial nuclear reactors. The objective of this thesis was the development of advanced methods for the in-core fuel management to improve the fuel cycle cost of PWR.

To accomplish this aim, the present thesis dealt with a following series of studies on the advanced in-core fuel management:

(1) A study on optimization methods of the loading pattern for the practical in-core fuel management of PWR,
(2) A development of software for the practical in-core fuel management of PWR, especially applicable to the multicycle analysis,
(3) A study on strategies of the loading pattern design, which takes into account the overall economics of multiple cycles.

The outline of this thesis and the results obtained in the course of this study are summarized as follows:

Chapter 1 described a brief explanation about the in-core fuel management of PWR and the optimization problem of the fuel loading pattern, to provide a basis for better understanding of the contents of this thesis.

Chapter 2 provided the results of a study on the optimization methods of the fuel loading pattern that has great effect on the safety and economics of the PWR core performance. As described in Chap. 1, practical results cannot be obtained through the traditional optimization methods such as the linear programming, since the loading pattern optimization method is essentially the combinatorial one and has many stiff natures. Therefore, the genetic algorithm was applied in this study to overcome these difficulties. The genetic algorithm is one of a stochastic optimization method, which simulates the evolution of life; it performs optimization through the survival of the fittest and breed improvement by the crossover of the chromosomes. Furthermore, a hybrid optimization method, which combines the genetic algorithm and the local search method, was newly proposed to improve the optimization capability.

A benchmark calculation was performed to make the quantitative comparisons of the optimization capability among several optimization methods. The simulated annealing, the genetic algorithm, the direct search, the binary exchange and the hybrid methods were examined through this benchmark problem. From the results of the benchmark calculation, the hybrid optimization method provided a superior loading pattern than the other methods. Furthermore, a required computation time was less than one-third of the alternative global optimization method, i.e. the simulated annealing. Since the hybrid optimization method can treat various constraints and objectives, it is useful for the practical in-core fuel management of PWR.

Chapter 3 describes a detailed benchmark calculation of the hybrid optimization method. A benchmark problem that contains almost 350,000 loading patterns was defined and exhaustive enumerated calculations were performed to

obtain the optimum solution. After that, the benchmark problem was analyzed using the hybrid optimization method. Though the number of calculated patterns by the hybrid optimization method was about 3,000, the hybrid method reached the optimum solution that was identified by the enumerated calculations. Since the probability to reach the optimum solution by a random search method with 3,000 trials is less than 1 % in this benchmark problem, the effectiveness of the hybrid optimization method was confirmed.

Chapter 4 treated the development of INSIGHT, which is a practical tool for the in-core fuel management of PWR. Though some researchers has developed this kind of software, INSIGHT has following distinguished features:

(1) Utilizes the hybrid optimization method for the efficient loading pattern design,
(2) Not only a single cycle, but also multiple cycles can be treated automatically,
(3) Integrates analysis capabilities and database to realize seamless and easy operation for users,
(4) Adopts the object oriented programming for the extensibility and maintainability.

INSIGHT has been applied to the practical problem that included optimization problems of a single cycle under various constraints and that of the multicycle under the constraint of burnup limitation at the RCC positions. These calculations were successfully performed and the capabilities of INSIGHT were confirmed.

Chapter 5 provided the study on the strategy of the loading pattern design, which took into account the multiple cycle. To simulate the nature of multiple cycles,

which is somewhat different from that of a single cycle, an equilibrium cycle was treated in this study. An optimization code for the equilibrium cycle was newly developed and used throughout this study. Using the equilibrium cycle optimization code and the multicycle optimization code developed in Chap. 4, several strategies of the loading pattern design were investigated.

In the test problem, the results provided the low-leakage loading pattern, which arranges burnt fuels at the core periphery to reduce the neutron leakage, was inferior to the partial out-in loading pattern, which puts burnt fuels inboard. The results also revealed that the low-leakage loading pattern is short term optimal; the optimal for the single cycle, otherwise the partial out-in loading pattern is a long-term optimum; the optimum for the multiple cycle. Consequently, to reduce overall fuel cost for multiple cycles, the discharge burnup maximization should be performed in each cycle, rather than the minimization of neutron leakage from the core.

Throughout this study, the optimization method for the in-core fuel management of PWR was developed and successfully applied to the practical problem. Furthermore, the optimization strategy not only for the single cycle but also for the multiple cycles was revealed. These results will contribute to improve the fuel cycle cost of nuclear reactors, which is one of the important points to reduce the cost of electricity.

A future view of study on the in-core fuel management optimization of PWRs, the following items would be necessary for instance:

(1) As described in Chapter 5, the "true multicycle optimization", which performs

the loading pattern optimization of multicycles simultaneously, is far beyond the ability of current computers, even for the today's high-performance ones. However, the true multicycle optimization is expected to provide more valuable information about the effective usage of nuclear fuel. Therefore, it is considered to be important to perform a study for establishing a computable model that can capture the essential characteristics of the true multicycle optimization.

(2) The hybrid genetic algorithm, which is described in Chapter 2, greatly reduces computation time and provides robust optimization capabilities for the practical problems of loading pattern optimization. However, since the hybrid genetic algorithm is one of the stochastic optimization methods, it still takes considerable computation time. Although several approaches may be available to achieve the further reduction in computation time, incorporation of the advanced knowledge processing such as the knowledge acquisition or the case based reasoning may be useful for the loading pattern optimization problems.

These studies may provide better results for the actual loading pattern optimization problems and may realize more efficient utilization of the nuclear fuel.

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